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Review

Three decades of gait index development: A comparative review of clinical and research gait indices

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ABSTRACT

Background: A wide variety of indices have been developed to quantify gait performance markers and associate them with their respective pathologies. Indices scores have enabled better decisions regarding patient treatments and allowed for optimized monitoring of the evolution of their condition. The extensive range of human gait indices presented over the last 30 years is evaluated and summarized in this narrative literature review exploring their application in clinical and research environments.

Methods: The analysis will explore historical and modern gait indices, focusing on the clinical efficacy with respect to their proposed pathology, age range, and associated parameter limits. Features, methods, and clinically acceptable errors are discussed while simultaneously assessing indices advantages and disadvantages. This review analyses all indices published between 1994 and February 2021 identified using the Medline, PubMed, ScienceDirect, CINAHL, EMBASE, and Google Scholar databases.

Findings: A total of 30 indices were identified as noteworthy for clinical and research purposes and another 137 works were included for discussion. The indices were divided in three major groups: observational (13), instrumented (16) and hybrid (1). The instrumented indices were further sub-divided in six groups, namely kinematic- (4), spatiotemporal- (5), kinetic- (2), kinematic- and kinetic- (2), electromyographic- (1) and Inertial Measurement Unit-based indices (2).

Interpretation: This work is one of the first reviews to summarize observational and instrumented gait indices, exploring their applicability in research and clinical contexts. The aim of this review is to assist members of these communities with the selection of the proper index for the group in analysis.

1. Introduction

Gait has long been established as the most performed task of human movement. As early as the Renaissance, basic human biomechanics were studied in order to understand the anatomy and elements of movement that factor into gait. Gait analysis, as we know, was established in the 1870s (Whittle, 1996). Nearly a century and a half of research has led to a great deal of progress in gait analysis, with dozens of gait indices now available not only to academic researchers but to physicians and physical therapists. Along with comparative observations of gait, advances in three different areas have contributed strongly to research on gait analysis and to the development of gait indices: kinematics, kinetics, and electromyography. However, despite the progress made in these areas of instrumented gait analysis, observational indices are still extremely popular within the clinical community.

1.1. *Observational and instrumented gait analyses throughout history*

The first scientific record of gait analysis dates back to the 4th century BC, when Aristotle wrote *De motu animalium* (Nussbaum, 1985). This study was based entirely on the observational analysis of the gait cycle. Following this, records show a strong foundation of observational biomechanics and gait analysis all throughout early history, particularly in the works of da Vinci, Galileo and Borelli (Whittle, 1996). As technology progressed, gait analysis and index development moved from purely observational to instrumented. The Weber brothers can be noted as one of the first to record quantitative studies of temporal and distance parameters during human locomotion (Andriacchi and Alexander, 2000). In the 1870s, Marey and Muybridge were the first researchers to incorporate instrumented technology into their analyses, with the purpose of extract kinematic data through the use of chronophotography, thereby bringing a new dynamics to gait analysis and to the

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development of gait indices (Whittle, 1996). Nowadays, instrumented gait analysis is recognized as the gold standard for evaluating locomotion and developing gait indices, being an essential tool to support clinical decision (Wren et al., 2020). However, despite being considered somewhat subjective and a weak alternative to instrumented gait analysis, observational gait tools are still widely used particularly for children (Rathinam et al., 2014; Toro et al., 2003). As results, various clinicians and researchers are combining observational and instrumented gait analysis methods in an effort to obtain well-rounded data (Viehweger et al., 2010).

1.2. Instrumented gait analysis: kinematics, kinetics and electromyography

Kinematic measurements, which generally refer to the acquisition and quantification of movement throughout a gait cycle, are one of the oldest forms of gait analysis measurements that exist (Whittle, 1996). These measurements focus on bodily movements without considering the forces involved during motion (Sutherland, 1997; Winter, 1991). Kinematic measurements can be taken from any recording device that can be linked into a computer (e.g., motion capture systems (MOCAP), inertial measurement units (IMUs), among others). This enables the evaluation of linear and angular displacements, velocities, and accelerations, while simultaneously allowing the computation of three dimensional movements of all major joints involved in the gait cycle (Winter, 1991). Within kinematic measurements, there is a subgroup known as time-distance parameters (TDP) that focuses on the analysis of the variation of spatial and temporal parameters, such as step/stride lengths/periods and cadence (Sutherland, 1997). TDP measurements are often found to be of clinical value and, for that reason, have been applied in gait quantitative indices (Cahill-Rowley et al., 2019; Gouelle et al., 2013; Nelson, 1974; Schutte et al., 2000).

Kinetic measurements focus on analyzing the external forces that may act on the body. This type of analysis makes use of force/pressure platforms or other similar force transducers (e.g., pressure insoles, dynamometers, etc.) to measure their magnitude, orientation and application point. Within the gait analysis field, ground reaction forces and foot pressure distribution stand out. The first group is required to understand the magnitude of the normal forces that act on the body and to solve the problem of undetermined force distribution during the double support phase, while the second one can be used to assess posture, balance and ankle-foot dynamics (Sutherland, 2005; Whittle, 1996; Winter, 1991).

The combination of both kinematic and kinetic data with user-specific anthropometric and topological information allows for the assembling and solution of the equations of motion of a given biomechanical system. As a result, the internal and state dependent forces associated with transmitted skeletal loads, joint contacts and ligament forces, and loads related to system activity (e.g. joint torques) can be computed (Ambrósio and Tavares da Silva, 2005; Winter, 1991). These techniques, alongside with optimization methodologies, control-based strategies, or electromyography (EMG), can be used to solve the problems related to redundant musculotendon forces, enabling the estimation of muscle activations and forces noninvasively (Ambrósio and Tavares da Silva, 2005; Oliveira et al., 2016; Xiang et al., 2010). Moreover, the inclusion of EMG data allows for the validation of the developed models (Quental et al., 2018).

Electromyography, which is the recording and measurement of electric activity within muscle tissue, is the most recent addition to gait indices development (Sutherland, 2001). As neural control of movement is irrevocably tied to actual movement, EMG analysis can be utilized to understand the agonistic or antagonistic activity in each muscle (Winter, 1991). As such, gait analysis utilizing EMG allows for an increasingly detailed study of motor patterns' dynamic properties, as well as information on fatigue states and muscle fiber types (Frigo and Crenna, 2009; Winter, 1991). EMG analysis is typically performed using surface electromyography (sEMG), a non-invasive procedure, rather than the invasive needle-electrode counter-part, facilitating the use of this technique in clinical and research environments (Frigo and Crenna, 2009).

1.3. Scope and key methodological concepts

Technological and mathematical advances in the 20th and 21st century have brought gait analysis to an all-time peak. The various combinations of the aforementioned data types have brought in a range of gait indices from hospitals and research groups worldwide. However, this abundance of gait indices generated a need for increased validation prior to clinical use. This narrative literature review aims to provide a broad summary of modern gait indices, identifying those of particular utility as well as those which should now be considered outdated or of limited use. It individually covers each selected index and analyzes its relevance in clinical and research environments, aiming to assist the members of these communities with the selection of the most suitable index. This work provides the reader with a comprehensive overview that integrates both observational and instrumented indices and updates the available information in this area with respect to previous reviews (Cimolin and Galli, 2014; Gor-García-Fogeda et al., 2016; Rathinam et al., 2014; Toro et al., 2003). The main advantages and limitations are explored considering these two settings, as each one requires different specifications and is usually composed by members with different backgrounds. Hence, the original pathologies, age targets and base methods are presented. Validity and reliability studies are also considered in order to understand the relevance and applicability of each index within varied environments, conditions, pathologies and age groups.

To cluster the indices, an initially division will be performed based on the type of methodology used for the scoring of the parameters that compose them. The indices will be grouped considering if their scoring relies only on observational features (observational indices) or uses quantitative metrics acquired using different systems (instrumented indices). On its turn, the instrumented indices will be posteriorly divided in sub-groups according to the nature of the patterns/parameters used in its definition: kinematic-, spatiotemporal-, kinetic-, kinematic- and dynamic-, electromyographic- and IMU-based indices.

Most instrumented indices addressed throughout this review have a critical statistical or mathematical component to them. Recent indices are increasingly utilizing advanced, interdisciplinary methods as means to better score gait. The key methodological concepts underlying the evaluation of these indices are briefly summarized hereafter to support readers from non-computational backgrounds.

Reliability tests are of particular interest as they allow for the inference of the agreement rate in the index scoring by a single observer (intra-rater/test-retest reliability) or by multiple raters (inter-rater reliability), providing a quantitative and qualitative measure of the index reproducibility. In turn, validity tests assess the index performance to the variable in analysis. Essentially, these tests evaluate the existence of correlations between the index output and criterion standards (criterion validity). This analysis is sometimes difficult as there are no criteria already established in literature. In this case, it is usual to recur to a constructed validity approach. For each condition/disorder, the index is tested to the existence of possible correlations with other measures, usually indices or scales already accepted by the medical and rehabilitation community (e.g. functional, mobility and balance scales or other gait indices) (Gor-García-Fogeda et al., 2016).

Principal component analysis (PCA) is a data analysis tool that allows for the conversion of a dataset of variables, which can be correlated, into a new set of linear uncorrelated variables. In fact, this procedure transforms a collection of experimental observations of a given subject into a set of uncorrelated and orthogonal vectors that can be linearly combined to represent him (Jollife and Cadima, 2016). Many modern indices use variations of PCA to make statistically better judgements on correlated measurements (Deluzio and Astephen, 2007; Muniz and Nadal, 2009; Romei et al., 2004; Schwartz and Rozumalski, 2008). An increasingly popular mathematical approach is the concept of automatic face matching, otherwise known as the Eigenface methodology. This concept involves calculating index values of subjects by projecting measurements onto the principle components of a control group and calculating Euclidean distance between the subject and an average control group member (Schwartz and Rozumalski, 2008). For example, Gait Deviation Index (GDI) is calculated considering joint angular displacements for ankle and knee. A subject with a limp will show deviation from the norm in both of these measurements at the same time as they are correlated. However, when comparing such subjects to healthy ones, it is unclear whether the ankle difference or knee difference is more important and how these measurements should be weighed. PCA resolves this issue by comparing approximations of each subject composed of imaginary, orthogonal, normalized variables (Schwartz and Rozumalski, 2008).

Inspired by the central nervous system, artificial neural networks (ANNs) represent a group of computational methodologies capable of performing machine learning and pattern recognition. By previously training a given ANNs model with a large database of inputs and the respective outputs, these methodologies can be used to predict the outcome of a given system from a set of known inputs. The accuracy of the prediction will be influenced by the quality and size of the training database, as well as the complexity and parameters used for the definition of the ANN model (e.g. topology, activation and cost functions, among other parameters) (Bishop, 1995). Like other statistical approaches, artificial neural networks allow for non-linear relationships and multiple types of input variables. ANN models have been widely used in various types of biomechanical studies, from balance control to movement analysis (Barton et al., 2007; Lugade et al., 2014). Particularly, when applied to gait assessment, ANNs can be trained using data from a control group to define an abstract representation of normality. By comparing it with the state vector that represents a pathological gait, these models allow for the quantification of the degree of abnormality, using, for instance, the Euclidian distance over time (Barton et al., 2007).

2. Methods

To provide a comprehensive overview on gait indices, a narrative literature review was conducted following the guidelines presented on PRISMA statement (Moher et al., 2009). The analysis considered all publications from June 1994 to February 2021 and used Medline, PubMed, ScienceDirect, CINAHL, EMBASE, and Google Scholar databases, as these contain the vast majority of literature on instrumented gait analysis. The keywords for the analysis were identified using MEDLINE thesaurus online and Medical Subject Headings (MeSH). The selected keywords used during the identification process were gait, locomotion, walking, biomechanics, observational, kinematics, kinetics, dynamics, and electromyography combined with the terms analysis, evaluation, and diagnostic techniques. The combined keywords gait analysis, gait index/indices, motion analysis, and biomechanical analysis were also used.

All studies found in literature presenting or discussing the reliability or validity of an index developed for the evaluation of gait performance were included in the eligibility analysis step. Studies applying indices for evaluation of abnormality in children (1-18 y/o), adults (19-64 y/o), and elderly adults (65+ y/o) with musculoskeletal, neurological, neuromuscular, rheumatological, or any other similar disorders that affect gait were also included in the initial selection. Any type of study found in literature reporting observational, kinematic, kinetic, electromyography, or IMU-based indices was initially considered. Hence, papers, commentaries or case studies published in scientific journals and posters or abstracts published in conference proceedings were included in the first screening process. On the other hand, non-published works, such as conference abstracts or posters, or other sources of unpublished data were not included in this analysis. Additionally, articles identified by the search were screened to ascertain that they were human-focused, i.e., no papers addressing animal or robotic gait were included in the analysis.

The identification and screening processes were performed by two independent researchers to avoid selection bias. The criteria defined for the acceptance or rejection of a given gait index had in in consideration its innovative aspect and its posterior relevance in the medical and scientific community. The adopted criteria defined eligible indices that evaluate gait performance in normal and pathological groups and present a historical relevance or are commonly applied/referenced in both observational and instrumented gait studies in these communities. Moreover, indices that explore different analytic items or present novel methodologies for gait assessment, which the authors believe can be relevant in the future, were also defined as an inclusion criterion. In order to be accepted, the items that compose the index should assess a set of gait patterns in specific instants or over the entire gait cycle. Therefore, observational and instrumented indices that evaluate kinematic-, spatiotemporal-, kinetic-/dynamic-, electromyographic- or IMU-related patterns in specific gait events or phases detailed in the index description or along the entire cycle were included in the study.

On the other hand, indices based on gait-related tasks or psychometric conditions were defined as exclusion criteria, i.e., functional scales that evaluate the response of an individual to a specific task (e.g., change the gait speed, increase the step/stride length, reverse the direction of walking, among others) or to different walking conditions (e.g., walk up/down stairs or step over/around an obstacle while walking) were rejected during the selection procedure. This way, performance tests such as the Dynamic Gait Index (Shumway-Cook and Woollacott, 1995), Gillete Functional Assessment Questionnaire (FAQ) (Novacheck et al., 2000), Gross Motor Function Measure (GMFM) (Russell et al., 1989) and its evolution Gross Motor Function Classification system (GMFCS) (Palisano et al., 1997), Functional Gait Assessment (Wrisley et al., 2004), tests that compare walking velocity, time, or distance (e.g. Time Up and Go (TUG) (Podsiadlo and Richardson, 1991), time to walk a fixed distance 3m, 6m, 40m, or 6 Minute Walk Test (6MWT), among others (Hayes and Johnson, 2003)) or the Tinetti Performance-oriented mobility assessment (POMA) (Tinetti, 1986) were not covered in this work.

This review portraits chronologically the evolution of the state of the art in gait index calculation over the last 30 years. Each index considered in the selection process is discussed individually, based upon the information detailed in the original literature supporting the index description and on other relevant conclusions presented in later works. The retrieved information focused on the applicability of the index in terms of pathology and age target, parameters and computational methodologies needed for its evaluation and reliability/validity analyses. The major limitations and advantages reported by other authors were also addressed during the index description.

Besides subject related factors, the selection of the most suitable index should also consider the type and the objective of the analysis. To assist in this selection, an analytic comparison, considering the intrinsic characteristics of both observational and instrumented indices, is also performed, highlighting their applicability in clinical and research environment.

3. Results

Due to the large number of works found using the search strategy proposed in section 2, a paper count was not performed in identification phase. From the analysis of the titles and abstracts and after duplication removal, 167 publications were considered relevant to the subject of this work, being their contents scrutinized. This analysis allowed to find 30 indices that satisfied the defined criteria and 137 more papers discussing significant aspects from the selected ones, as reliability, sensitivity and validity analyses. The selected indices were divided in three major groups according their application: observational-based (13), instrumented-based indices (16) and hybrid indices (1). In addition, the instrumented-based indices were also subdivided in six groups, based on the nature of the items that compose them: kinematics (4), spatiotemporal (5), kinetics (2), kinematics and dynamics (2), electromyographic (1) and IMU-based (2) (see Fig. 1).

The identified indices are presented chronologically according to the division presented before (see Fig. 2). A summary of their major characteristics, focusing on the nature of the features used in its scoring, the statistical method applied to obtain the final index, items description and original target group, are presented on Table 1 (instrumented) and Table 2 (observational and hybrid), displayed in the end of section 3.1.10 and 3.8 respectively. The major conclusions and issues reported in the original manuscript, regarding index applicability and methods, inter- and intra-rater reliability, sensitivity and criterion validity, are also presented on both tables. In order to increase the readability of this manuscript, a list of all acronyms used along the review is presented in Supplementary Materials section (see SM1).

3.1. *Observational indices*

Clinically, observational indices have substantial value as they are cost effective, user-friendly, and can be easily used in various age groups (Rathinam et al., 2014). Observational indices are even the preferred choice for young children, partially because of difficulties of performing valid three-dimensional (3D) analyses due to the typical behavior of this age group (Boyd et al., 1999; Harvey and Gorter, 2011; Mackey et al., 2003). Despite the widespread use of these indices, they are often recognized as highly subjective and even potentially inaccurate (Bella et al., 2012; Toro et al., 2007a). This review did not assess the validity of each observational index, but instead summarizes reported findings of other literature on observational index validity and shortfalls.

3.1.1. *Physician's Rating Scale (PRS)*

The Physician's Rating Scale, created in 1993, is one of the earliest modern observational gait indices. It was initially developed to analyze children with cerebral palsy (CP). PRS involves videotaping subjects walking from several angles, while a clinician visually and manually analyses the recordings (Koman et al., 1993). This allows for clinicians to score the patients numerically on various aspects of their gait, based on six assessed parameters per leg that includes hip, knee, ankle and foot kinematic features and gait speed. Each index parameter has its own defined category and score, yielding in an overall score that ranges

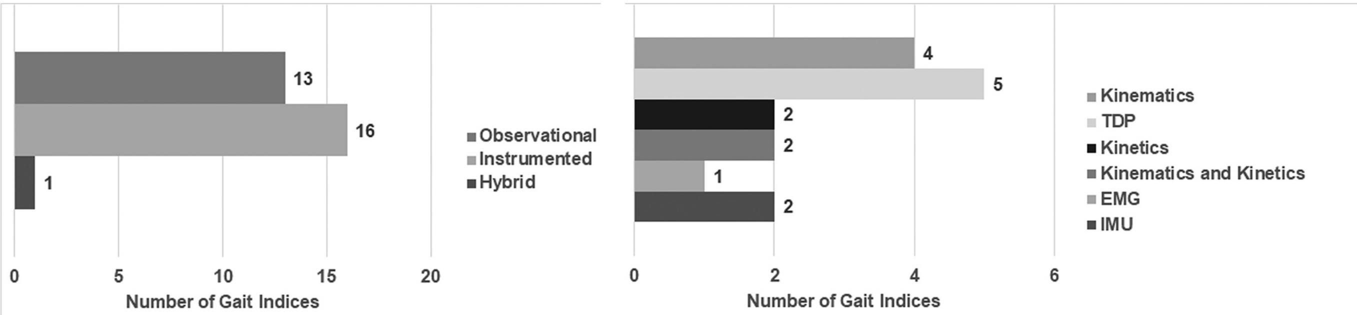

Fig. 1. – Number of indices identified during the screening and eligibility process considering: the type of methodology used to score them (left); the nature of the features used in their definition (instrumented indices) (right).

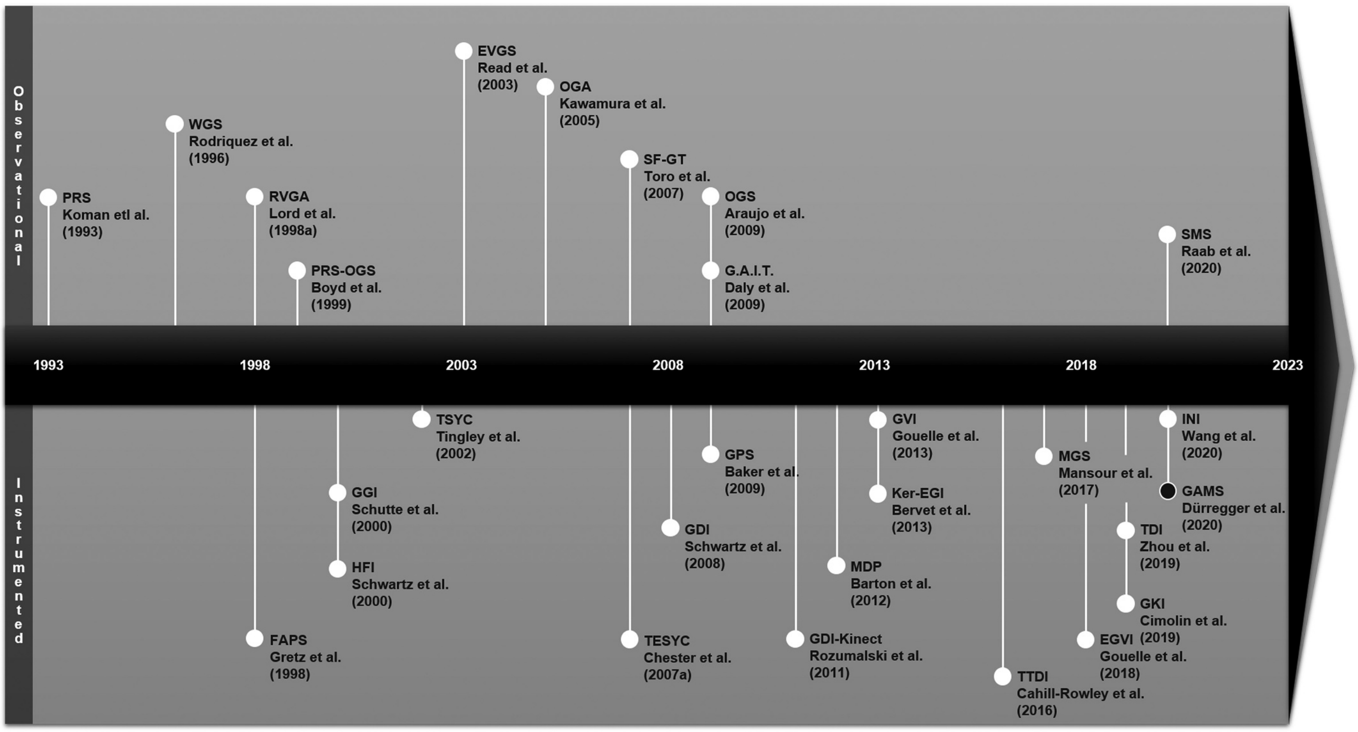

Fig. 2. – Timeline presenting the three decades of gait indices development (black dot represents a hybrid index).

Table 1
– List of the observational indices and their major characteristics identified during the screening step: Original Work, Study Design, Statistical Method, Items Description; Original Target Group and Main Results (Intra- and inter-rater reliability, validity and sensitivity).

Index Name (Original Work)	Study design	Statistical method	Items description	Original target group	Main results
PRS (Koman et al., 1993)	- Experimental (One Group Pre- & Post-Treatment Design (follow-up)) - Prospective Pilot Study	multi-point scale	6 gait features	Pediatric population with CP	- Sensitive to detect differences between pre- and post-intervention (Botox treatment) ($p < 0.05$);
PRS-OGS (Boyd et al., 1999; Boyd and Graham, 1999)	- Experimental (Case Studies) - Prospective Study	multi-point scale	8 gait features per leg	Pediatric population with CP	- Clinical protocol for objective evaluation of clinical findings in patients subjected to a botulinum toxin type A intervention in children with CP; - Present a modified version of PRS scale to improve the index sensitivity to the applied intervention; - Sensitive to detect differences between the "true *equinus*" and "apparent *equinus*" cases; - Significant differences between pre- and post-intervention ($p < 0.01$); - High inter-rater reliability, presenting a maximum deviation value of 26% of the subject's mean score (Kendall's τ-B: ranged from 0.44 for hip extension to 0.88 in the use of gait aid);
WGS (Rodriquez et al., 1996)	- Experimental (Uncontrolled Case Series) - Prospective Study	weighted multi-point scale	14 gait features per leg	Hemiplegic patients recovering from a stroke event	- Sensitive to detect differences due to a home-based rehabilitation program in chronic hemiplegia patients ($p < 0.05$). However, only 3 features presented significant differences between pre- and post-training scores ($p < 0.05$); - WGS items related to the stance phase improved more after the training when compared with the swing phase ones;
RVGA (Lord et al., 1998a)	- Methodological (Reliability, validity and sensitivity to change: Test-retest) - Prospective Study	four-point scale	20 kinematic features	Adult population with different neurological disorders	- Pre-training scores presented an association with the ratings on Physical Functioning measure, indicating that the WGS score relates to the subject's appraisal of their own physical limitations; - Good intra-rater reliability (LSD: 10.5); - Good inter-rater reliability both for the global score (Kendall's $W = 0.84$) and for the individual items (exact agreement: 63.8%, Δ1 point: 28.8%, Δ2 points: 6.1%; Δ3 points: 1.2%); - Agreement rate improved when the rater performed a short training on the use of the index (~10 min); - Agreement rate improved when a 3-point ordinal scale was used. However, it can decrease the sensitivity of the index to gait changes, reducing its validity; - Significant correlations with walking time ($\rho = 0.77$) and stride length ($\rho = -0.61$); - Sensitive to detect differences between the pre- and post-intervention ($p < 0.01$); - Significant correlations with other scores used to assess MS treatment (Berg balance $\rho = -0.79$; RMI pre-intervention $\rho = -0.68$ and RMI post-intervention $\rho = -0.75$); - Significant correlation with the change in walking time of patients with mobility problems undergoing physical rehabilitation sessions ($r = 0.68$); - Good Intra-rater reliability (Mean LSD: 3.20 (ranging from 2.63 to 4.01));
EVGS (Read et al., 2003)	- Methodological (Reliability, validity and sensitivity to change: Test-retest) - Prospective Study	three-point scale	17 kinematic features	Pediatric population with CP	- Good inter-rater reliability both for the global score (70% MAR) and for the individual items, which ranged from a 55% agreement rate ($\kappa = 0.17$) in knee extension in terminal swing to 96% ($\kappa = 0.94$) in the type of foot-ground contact during the initial contact; - Higher inter-rater agreement in sagittal items ($\kappa = 0.46$) when compared to coronal items ($\kappa = 0.35$); - Fair agreement with instrumented data (64% MAR), which ranged from a 47% agreement rate for the maximum knee extension during stance phase to 83% for the maximum ankle dorsiflexion in swing phase;
OGA (Kawamura et al., 2007)	- Methodological (Reliability and validity: Test-retest) - Retrospective Study	three-point scale	10 kinematic features	Pediatric population with CP	- Sensitive to detect changes between pre- and post-surgery (no statistical data provided); - Fair to substantial inter-rater reliability, ranging from a 52.9% diagonal agreement (McN test) in the Knee flexion at initial swing ($\kappa_{LS} = 0.31$, $\kappa_{RS} = 0.32$) to 98.0% in the ankle dorsiflexion at initial contact ($\kappa_{LS} = 0.74$, $\kappa_{RS} = 0.88$); - Only 2 of 10 parameters presented a moderate or better agreement with instrumented data: Knee flexion at initial contact ($\kappa_{LS} = 0.47$, $\kappa_{RS} = 0.65$) and Pelvic obliquity ($\kappa = 0.51$);

(*continued on next page*)

Table 1 (*continued*)

Index Name (Original Work)	Study design	Statistical method	Items description	Original target group	Main results
SF-GT (Toro et al., 2007a; (Toro et al., 2007b)	- Methodological (Reliability, validity and masked comparative evaluation: Test-retest) - Retrospective Study	five-point scale	18 kinematic features	Pediatric population with CP	- Fair agreement with instrumented data (58% MAR), ranging from 28% to 75% agreement rate. 95% of the disagreements differed by 1 category, 4% by 2 and 1% by 3 categories; - An LSD of 16.25° was achieved between the raters score and instrumented data, with 80% of the observations laying within this range; - Good intra-rater reliability for the global score (75% MAR), ranging from 66% to 87%. 97% of disagreements differed by 1 category, 2.4% by 2 and 0.3% by 3 categories; - Good inter-rater reliability for the global score (77% MAR), ranging from 67% to 83% agreement rate. 98% of disagreements differed by 1 category and 2% by 2; - Knee parameters presented a better accuracy (MAR ankle: 56%; knee: 61% and hip: 58%), intra-rater (MAR ankle: 73%; knee: 78% and hip: 72%) and inter-rater agreement (MAR ankle: 75%; knee: 81% and hip: 77%) than hip and ankle variables;
OGS (Araújo et al., 2009)	- Methodological (Reliability and validity: Test-retest) - Prospective Study	-	24 kinematic features	Pediatric population with CP	- Very good intra-rater reliability for the overall index ($w\kappa = 0.74$). 4 items achieved an excellent agreement, 11 a very good and the remaining 8 a good intra-rater agreement; - The analysis of the intra-rater reliability per joint showed a better agreement for ankle-foot complex, followed by knee, hip and pelvis (ankle-foot complex: $w\kappa = 0.79$, knee: $w\kappa = 0.77$, hip: $w\kappa = 0.73$, pelvis: $w\kappa = 0.59$); - Very good inter-rater reliability for ankle-foot complex ($w\kappa = 0.68$) and knee ($w\kappa = 0.65$), good for hip ($w\kappa = 0.48$) and fair agreement for pelvis segment ($w\kappa = 0.30$); - Of the 4 raters, 1 presented a good agreement with instrumented data ($w\kappa = 0.40$) and the remaining 3 achieved a fair agreement ($w\kappa$: 0.37 to 0.39); - Very good agreement with instrumented data for knee ($w\kappa = 0.64$), good for ankle-foot complex ($w\kappa = 0.59$) and poor to fair agreement for pelvis ($w\kappa = 0.20$) and hip ($w\kappa = 0.23$);
G.A.I.T. (Daly et al., 2009)	- Methodological (Reliability and validity: Test-retest) - Retrospective Study	four-point scale	31 kinematic features	Subjects recovering from stroke events	- Good intra-rater reliability (ICC: 0.98 (CI: 95%)); - Good inter-rater reliability (ICC: 0.83 (CI: 95%)); - Good inter-rater reliability for an inexperienced rater, who received training on the use of the index, with experienced raters (ICC: 0.996 (CI: 95%)); - Good agreement with instrumented data for the 2 analyzed items: Knee flexion at toe-of ($\rho = 0.65$) and peak knee flexion during swing phase ($\rho = 0.76$); - Sensitive to detect changes in the gait patterns for the 2 tested interventions (comprehensive gait training ($z = -2.93$, $p = 0.003$) and comprehensive gait training with functional electrical stimulation ($z = -3.3$, $p = 0.001$). G.A.I.T. was also sensitive to identify differences between the 2 interventions ($p = 0.021$);
SMS (Raab et al., 2020)	- Methodological (Reliability and validity: Test-retest) - Prospective Study	four-point scale	6 gait features	Subjects recovering from stroke events	- Observational score based on non-redundant items (Spearman's cross correlation between items ranged from 0.50 to 0.72); - High consistency (Cronbach's $\alpha > 0.9$) and excellent inter-rater reliability for the overall index (ICC: 0.894) and good to excellent for the individual scores (ICC ranged from 0.601 for trunk posture to 0.842 for stability/risk of falling); - Moderate correlation with other scores applied in stroke rehabilitation (10m Walk-Test: $\rho = 0.59$; TUG: $\rho = 0.52$; NIHSC: $\rho = 0.53$; Berg Balance Scale: $\rho = -0.46$; FIM – Item L: $\rho = -0.43$; Barthel Index: $\rho = -0.42$); - 2 of the 6 items presented a good correlation with the 10m Walk-Test (Gait speed: $\rho = 0.63$; Gait fluency: $\rho = 0.63$). Weak to moderate correlation between SMS items with other scores applied in stroke rehabilitation (TUG, NIHSC, Berg Balance Scale; FIM – Item L; BI);

Abbreviations and Acronyms
Indices: PRS – Physician's Rating Scale; PRS-OGS – PRS-Based Observational Gait Scale; WGS – Wisconsin Gait Scale; RVGA – Rivermead Visual Gait Assessment; EVGS – Edinburgh Visual Gait Score; OGA – Observational Gait Analysis; SF-GT – Salford Gait Tool; OGS – Observational Gait Scale; G.A.I.T. – Gait Assessment and Intervention Tool; SMS – Stroke Mobility Score;
Statistics: p – p-value; τ-B – Kendall's tau-b correlation coefficient; LSD – Least Significant Difference; W – Kendall's coefficient of concordance; ρ – Spearmen correlation coefficient; r – Pearson coefficient; MAR – Mean Agreement Rate; κ – Cohen's kappa coefficient; McN – McNemar test; wk – Weighted kappa coefficient; ICC – Intraclass Correlation Coefficient; CI – Confidence Interval; z – Wilcoxon Signed Ranks test z-value;
Comparative Indices/Scales: RMI – Rivermead Mobility Index; TUG – Time Up and Go; NIHSC – National Institutes of Health Stroke Scale; FIM – Functional Independence Measure; BI – Barthel Index for Activities of Daily Living;
Others: CP – Cerebral Palsy; MS – Multiple Sclerosis; LS/RS – Left/Right Side.

Table 2
– List of the instrumented indices and their major characteristics identified during the screening step: Original Work, Study Design, Index Type (nature of the items that compose the index), Statistical Method, Items Description; Original Target Group and Main Results (Intra- and Inter-rater reliability, validity and sensitivity).

Index Name (Original Work)	Study design	Index type	Statistical method	Items description	Original target group	Main results
GGI (NI) (Schutte et al., 2000)	- Methodological (Observational) - Retrospective Study	Kinematic	PCA	13 discrete kinematic features in specific events and 3TDP (per leg)	Children and adolescents with CP	- PCA is used to derive 16 independent gait variables; - Score provides a measure of the deviation of the subject's gait in relation to a control group, calculated as the sum of the Euclidian distance between the subject's data and the same uncorrelated variables for the mean of the normal population; - Score for the control group followed a χ^2 distribution; - GGI scaled with the increase of the topographic CP classification in hemiplegia types (I-IV), presenting a wide range of values for each group (no statistical significance);
TSYC (Tingley et al., 2002)	- Methodological (Observational) - Retrospective Study	Kinematic	Data Reduction Technique (Fourier Transform), PCA	36 discrete features expressing joint angles and derivatives in sagittal plane (per leg)	Young children up to 7 y/o who were born prematurely	- Data reduction technique based on Fourier Transform, with equal number of coefficients for each gait cycle, and PCA to select the most relevant variables; - Score considers joint angles and their derivatives in sagittal plane and represents the square distance between the subject's gait and the control group; - Score labels subject's gait as normal, unusual or abnormal; - Data can be reduced to 11 interpretable functions that express 70% of the data variability;
GDI (Schwartz and Rozumalski, 2008)	- Methodological (Observational) - Retrospective Study	Kinematic	PCA, RMSD, Logarithmic transformation, Z-Score	15 kinematic features along the gait cycle	Overall gait performance (validated in a CP population)	- Eigenface method (PCA) is used to derive 15 uncorrelated variables that express 98% of the data variation; - Logarithmic transformation and z-score conversion are applied to define an overall score, in which 100 points represent the mean value for the control group and every 10 points below this value express one STD of the mean; - Fair correlation with GGI ($r^2 = 0.56$); - GDI scaled with the increase of the FAQ levels 6 to 10 ($p < 0.05$); - Normally distributed for FAQ levels 6 to 10 and for the control group (K-S test: $p < 0.05$); - GDI score decreased with the increase of the topographic CP classification in hemiplegia types (I-IV) and was able to distinguish between affected and contralateral side. It also showed a correlation with the diplegia, triplegia and quadriplegia conditions in a CP population;
GPS (MAP and GVS) (Baker et al., 2009)	- Methodological (Observational) - Retrospective Study	Kinematic	RMSD	Set of kinematic features along the gait cycle (MAP: 9 selected parameters for both legs)	Overall gait performance (validated in a pediatric population with CP and general orthopedic conditions)	- General score (GPS) representative of the overall gait performance and a map profile (MAP) to evaluate individually the variation of 9 kinematic variables (GVS) for both legs; - GPS and GVS are calculated as the Euclidean distance between the subject/group in analysis and the control group; - Low intra-session variability (Mean IQR: 0.67°); - Moderate correlation with GGI ($\rho = 0.79$) and very strong correlation with GDI ($r = 0.995$), being more suitable for smaller datasets; - GPS does not present a normal distribution for FAQ levels 6 to 10 and GMFCS I to III (K-S test: $p < 0.05$);

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Index Name (Original Work)	Study design	Index type	Statistical method	Items description	Original target group	Main results
						- Weak correlation with walking speed ($\rho = -0.28$), indicating that these two measures can be used in a complementary way; - GPS and GVS do not present a strong correlation between them (ρ ranged from 0.47 for pelvic obliquity, hip abduction and hip rotation to 0.72 for knee flexion);
FAPS (Nelson, 1974)	- Methodological (Descriptive - Test-Retest (4x)) - Prospective Study	TDP	Descriptive statistics	6 TDP	Neuromuscular and Musculoskeletal disorders	- General score based on TDP; - High intra-rater reliability (Immediate Test-retest: *r*: 0.913 to 0.998; Two-week test-retest: *r*: 0.896 to 0.902); - High inter-rater reliability (*r*: 0.896 to 0.945); - High inter-session reliability (ICC: 0.91); - MDC (CI 95%): 8.6; - SEM (CI 95%): 3.1;
GVI (Gouelle et al., 2013)	- Methodological (Observational) - Retrospective Study	TDP	PCA, RMSD, Logarithmic transformation, Z-Score	9 TDP per leg	Friedreich's Ataxia	- Moderate correlation with ICARS scale ($r^2 = 0.29$) - Sensitive to distinguish different severity levels in FRDA patients according to the PGD sub-scores ($r^2 = 0.46$); - Moderate correlation with FAPS ($r^2 = 0.32$) and 8m walk test time ($r^2 = 0.33$);
EGVI (Gouelle et al., 2018)	- Methodological (Observational) - Retrospective Study	TDP	PCA, RMSD, Logarithmic transformation, Z-Score	6 TDP per leg	FRDA, children, older adults and Parkinson's disease)	- Enhanced version of GVI taking into account its reported limitations (magnitude problem and lack of direction specificity); - Better differentiation of different severity levels in pathological group when compared with GVI; - Very strong correlation with GVI ($r^2 = 0.95$); - Moderate correlation with FAPS ($r^2 = 0.22$), 8m walk test time ($r^2 = 0.31$), ICARS ($r^2 = 0.27$) and PGD subscale ($r^2 = 0.38$); - Fair to strong correlations with several functional scales (e.g., Berg scale, MiniBESTest and TUG);
TTDI (Cahill-Rowley and Rose, 2016)	- Methodological (Observational) - Retrospective Study	TDP	MSA, PCA, RMSD, Logarithmic transformation, Z-Score	7 TDP	Toddlers (18- to 22-month-old)	- Sensitive to detect differences on a population of preterm toddlers with different BSID-III gross motor scores (BSID-III ≥ 85 / CG: $p = 0.046$; BSID-III < 85 / CG: $p < 0.001$; BSID-III ≥ 85 / BSID-III < 85: $p = 0.004$); - Moderate correlation with BSID-III gross motor score ($r = 0.60$);
TDI (Zhou et al., 2019)	- Methodological (Observational) - Retrospective Study	TDP	MSA, PCA, RMSD, Logarithmic transformation, Z-Score	9 TDP	Pediatric population with CP	- General pediatric index based on TTDI methodology; - First 6 principal components described over than 98% of the original data variance; - Sensitive to detect differences on a population of children with CP ($p < 0.001$); - Strong correlation with GDI ($r = 0.610$); - TDI scaled with GMFCS levels I to III (not significantly different $p = 0.15$); - Sensitivity and specificity to gait function, evaluated through comparison with GDI in a population with a score lower than 80 points, was respectively 0.78 and 0.88;
GDI-Kinetic (Rozumalski and Schwartz, 2011)	- Methodological (Observational) - Retrospective Study	Kinetic	PCA, RMSD, Logarithmic transformation, Z-Score	20 kinetic features	Overall gait performance (validated in a CP population)	- Index based on GDI methodology; - 20 gait features described 91% of the original data variance; - Linearly related with GDI ($p < 0.01$), despite presenting a weak correlation ($r^2 = 0.24$); - GDI-Kinetic scaled with FAQ levels 6 to 10 ($p < 0.01$) and

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Table 2 (*continued*)

Index Name (Original Work)	Study design	Index type	Statistical method	Items description	Original target group	Main results
						with topographic CP classification in hemiplegia types (I-IV), diplegia, triplegia and quadriplegia;
GKI (Cimolin et al., 2019)	- Methodological (Observational) - Retrospective Study	Kinetic	RMSD, MDC normalization	6 kinetic features per leg (torques and mechanical powers in sagittal plane)	Children with diplegic CP	- Normally distributed for FAQ levels 6 to 10; - Unaffected limb presented a score lower than the one obtained for the affected side in hemiplegic subjects; - Index based on GPS methodology; - General score (GKI) representative of the overall gait performance, two sub-scores that evaluate the variables related to joint torques (GKI moment) and to joint mechanical power (GKI power) and a map profile (sub GKI) to evaluate individually the variation of 6 kinetic variables for both legs; - Sub GKIs are normalized considering its MDC to allow for the direct comparison of the features with different units; - Sensitive to detect differences between CP patients and the control group ($p < 0.05$) - Linearly related with GPS ($p < 0.05$), despite presenting a weak correlation ($\rho = 0.39$); - MDC for the GKI moment and GKI power was respectively 0.28 (ICC: 0.88) and 1.28 (ICC: 0.83) for the CP Group; - Linear relationship between the selected gait variables;
HFI (Schwartz et al., 2000)	- Methodological (Observational) - Retrospective Study	Kinematic and Kinetic	PCA	5 discrete kinematic and kinetic features in sagittal plane	Hip and pelvis performance (validated in a CP population)	- 75% agreement with subjective clinical evaluation; - Linear association ($\rho = 0.971$) and strong agreement (75%) between HFI and subjective clinical evaluation;
TESYC (Chester et al., 2007a, 2007b)	- Methodological (Observational) - Prospective Study	Kinematic and Kinetic	Data Reduction Technique (Fourier Transform)	TSYC plus kinematic, spatiotemporal and kinetic parameters	Extended original TSYC to children up to 13 y/o	- MDC: 1.62 (CI: 95%); - Index based on TSYC methodology; - Composed of 7 sub-indices (TSYC, Trunk Index of Gait, Kinematic Extra Index of Gait and 4 different kinetic gait indices) and an overall gait score (TESYC); - Score labels subject's gait as normal, unusual or abnormal; - Sensitive to identify differences on gait patterns for immature normative children (85%) and hypotonic children (100%);
MDP (Barton et al., 2012)	- Methodological (Observational) - Retrospective Study	Kinematic and Kinetic	ANNs - Self Organizing Map	Any kinematic, kinetic or EMG gait feature;	Overall gait performance (validated in a pediatric population with CP considering only kinematic patterns)	- Index described as a curve representative of the subject's gait distance to normality along the gait cycle; - Overall gait score described as the mean value of the MDP curve (mean MDP); - Applicable to any data expressed as a curve (e.g., EMG, ECG, etc.); - High correlation with GDI ($r^2 = 0.927$); - Sensitive to detect differences between CP patients with FAQ levels 7 to 10 ($p < 0.03$); - Mean MDP value scaled with the increase of the topographic CP classification in hemiplegia types (I-IV), diplegia, triplegia and quadriplegia;
KeR-EGI (Bervet et al., 2013)	- Methodological (Observational) - Prospective Study	EMG	PCA, RMSD, Logarithmic transformation, Z-Score conversion	7 EMG gait patterns	Overall gait performance (validated in an adult population of patients with several central nervous disorders)	- Index based on GDI methodology; - 14 eigenvectors described 98% of the gait variability; - Good repeatability between trials (repeatability index = 3.2%); - Fair to good correlation with GDI ($r^2 = 0.42$), GGI ($r^2 = 0.62$) and EVGS ($r^2 = 0.69$);

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Table 2 (*continued*)

Index Name (Original Work)	Study design	Index type	Statistical method	Items description	Original target group	Main results
MGS (Mansour et al., 2017)	- Methodological (Descriptive - Test-Retest (2x)) - Prospective Study	IMU	PCA, Z-Score conversion	6 sub-scores based on IMU measurements (computed using 10 features)	Overall gait performance (validated in a healthy adult, sedentary old adult and active old adult population)	- Global score defined as the mean of 6 partial scores that evaluate individually regularity, symmetry, temporal, distribution, amplitude and complexity; - Experimental data acquired using 1 IMU located at L3-L4 inter-vertebral level; - First 8 principal components described 84% of the original data variance; - Excellent inter-session reliability for global score (IC: 0.93; % SEM: 10.81); - Excellent inter-session reliability for 4 partial scores (temporal (ICC: 0.91; % SEM = 19.44), complexity (ICC: 0.87; % SEM = 35.46), amplitude (ICC: 0.97; % SEM = 17.99) and distribution aspects (ICC: 0.91; % SEM = 31.35)) and fair to good for 2 partial scores (symmetry (ICC: 0.64; % SEM = 13.83) and regularity (ICC: 0.70; % SEM = 32.40));
INI (Wang et al., 2021)	- Methodological (Experimental - One Group Pre-Treatment & Post-Treatment Design (follow-up)) - Prospective Study	IMU	PCA, RMSD	3 TDP and 6 kinematic features per leg	Validated in a population of individuals suffering from N-hexane neuropathy	- Sensitive to detect differences between the assessed groups ($p < 0.05$); - Experimental data acquired using 2 IMUs located near the ankle in both limbs; - Sensitive to detect improvements of the targeted intervention in the pathological population; - 8 of the 9 selected parameters presented statistical differences between the control and pathological group before the intervention ($p < 0.05$); - 7 of the 9 parameters presented statistical differences between the pre- and post-intervention in the pathological group ($p < 0.05$);
GAMS (Dürregger et al., 2020)	- Methodological (Observational) - Pilot Retrospective Study	Hybrid (observational and instrumented)	2-point scale	10 observational items for both legs and 5 instrumented TDP and Kinetic parameters)	Population of individuals recovering from a lower limb or spinal surgical intervention	- Hybrid index including observational and instrumented variables; - Excellent overall inter-rater reliability for the overall score (ICC: 0.98 (CI: 95%); RA: 86.1%) and for the observational variables (ICC: 0.97 (CI: 95%); RA: 82.5%);

Abbreviations and Acronyms

Indices: GGI – Gillette Gait Index; NI – Normalcy Index; TSYC – Tingley's Scale for Young Children; GDI – Gait Deviation Index; GPS – Gait Profile Score; MAP – Movement Analysis Profile; GVS – Gait Variable Score; FAPS – Functional Ambulation Performance Score; GVI – Gait Variability Index; EGVI – Enhanced GVI; TTDI – Toddle Temporal-Spatial Deviation Index; TDI – Pediatric Temporal-Spatial Deviation Index; GKI – Gait Kinetic Index; HFI – Hip Flexor Index; TESYC – Tingley's Extended Scale for Young Children; MDP – Movement Deviation Profile; KeR-EGI – Kerpape-Rennes EMG-based Gait Index; MGS – Multifeature Gait Score; INI – IMU-based Gait Normalcy Index; GAMS – Gait Analysis and Motion Score

Statistics: PCA – Principal Component Analysis; χ^2 – Chi-squared distribution; r^2 – Coefficient of determination; STD – Standard Deviation; p – p-value; K-S – Kolmogorov-Smirnov test; IQR – inter-quartile ranges; ρ – Spearmen correlation coefficient; r – Pearson coefficient; ICC – Intraclass Correlation Coefficient; CI – Confidence Interval; MDC – Minimum Detectable Change; SEM – Standard Error of Measurement; RA – Rating Agreement

Comparative Indices/Scales: FAQ – Gillette Functional Assessment Questionnaire; GMFCS – Gross Motor Function Classification System; ICARS – International Cooperative Ataxia Rating Scale; PGD – Posture and Gait Disturbance; TUG – Time Up and Go; BSID-III – Bayley Scales of Infant and Toddler Development - 3rd version;

Others: CP – Cerebral Palsy; FRDA – Friedreich's Ataxia; TDP – Time-Distance Parameters; EMG – Electromyography; ECG – Electrocardiography; IMU – Inertial Measurement Unit.

between 1 and 26 (Koman et al., 1993; Rathinam et al., 2014). Over the last 20 years, PRS has been modified by various authors and used as a foundation to develop new observational gait indices, such as the PRS-based Observational Gait Scale and Visual Gait Analysis Scale (VGAS) (Boyd and Graham, 1999; Dickens and Smith, 2006; Mackey et al., 2003).

Although PRS has a strong historical value, few works apply the original version, being used essentially for comparison or validation of novel observational indices. This is particularly due to the lack of standardization and uniformity in its scoring system, leading to questionable inter-observer reliability and validity (Maathuis et al., 2005; Rathinam et al., 2014). Consequently, various studies have recently changed their focus to assess and validate the various modified, abbreviated, and extended versions of the original PRS (Brown et al., 2008; Dickens and Smith, 2006; Wren et al., 2005).

3.1.2. PRS-Based Observational Gait Scale (PRS-OGS)

The PRS-Based Observational Gait Scale, defined as such to differentiate it from the Observational Gait Scale presented in (Araújo et al., 2009), was created as a modified version of the original PRS, also for use with children suffering from CP (Boyd et al., 1999; Boyd and Graham, 1999). PRS-OGS evaluates eight parameters that assess knee, ankle, foot progression and the use of gait assistive devices, scoring a maximum off 22 per leg. Additionally, as PRS-OGS was focused on the use of botulinum toxin type A as a therapeutic agent, index alterations were made to express the changes that were expected to occur (Boyd et al., 1999; Boyd and Graham, 1999; Mackey et al., 2003). Both the therapeutic and index outlined by Boyd et al. have remained quite popular over the last decade.

Mackey et al. assessed the PRS-OGS index for inter-rater and intra-rater reliability as well validity in comparison to 3D-gait analysis (Mackey et al., 2003). Their assessment showed an acceptable intra- and inter-reliability and validity for most knee and foot aspects, but poor intra- and inter-rater reliability for two sections of the index (base of support and hind foot position in stance), suggesting that these parameters should be reevaluated. However, this study was performed on older children, which the authors note as a potentially confounding factor as young children (between the ages of 2 and 6) were the main target of Boyd et al. original study (Boyd et al., 1999; Mackey et al., 2003).

3.1.3. Wisconsin Gait Scale (WGS)

Wisconsin Gait Scale is an observational index developed in 1996 to assess the evolution of gait performance in hemiplegic patients recovering from a stroke event (31-78 y/o). In its definition, WGS considers a weighted ordinal scale that focus on the affected leg. Considering a total of 14 items, it evaluates trunk, pelvis and lower limbs kinematics, as well as walking strategies and use of assistive devices (Rodriquez et al., 1996).

The index was firstly applied in the study of the evolution of hemiplegic patients subjected to a gait training program. WGS proved to be sensitive to detect differences in the global score after therapeutic intervention. When compared with the physical functioning scale, WGS presented a fair correlation for the evaluation performed before the first training sessions. However, this relation was not found when post-training data was considered. In the same study, the authors analyzed the index for its inter-rater reliability. The results indicated a fair to good agreement rate, observing lower values for the items: hip extension during toe-off and foot circumduction and toe clearance in swing phase (Rodriquez et al., 1996). Yaliman et al. and Wellmon et al. also assessed the WGS index for its reliability, obtaining a good to excellent score for both intra and inter-rater analysis (Wellmon et al., 2015; Yaliman et al., 2014). Similarly to the results presented in the original work, lower reliability values were found in foot circumduction, hip extension in toe-off and hip hiking at mid-swing (Yaliman et al., 2014). Also studying the outcome of training programs in hemiplegic patients, Turani et al. and Pizzi et al. showed that WGS is sensitive to detect variations in gait performance. Both studies indicate that WGS is a valuable index to characterize the level of abnormality in hemiplegia and to assess performance progress, particularly when used alongside with TDP measures, as its global score is fairly correlated with walking speed and stride time (Pizzi et al., 2007; Turani et al., 2004).

3.1.4. Rivermead Visual Gait Assessment (RVGA)

Presented in 1998, the Rivermead Visual Gait Assessment is a four-point ordinal scale designed to assess the walking impairments of patients suffering from different neurologic conditions. In its definition, RVGA considers 20 items that evaluate the kinematics of the upper limbs, trunk and lower limbs for the affected side during both stance and swing phase. In cases of bilateral disorders, the index is applied independently in both sides. RGVA reflects the intent of being a general measure of neurologic gait disorders. The choice of the items had in consideration the reported variations observed in patients suffering from these conditions. It is however noted that some relevant parameters may not have been included, suggesting a reevaluation of the items in order to extend its use to more neurologic and musculoskeletal conditions (Lord et al., 1998a). The index was tested by the authors to reliability, validity and sensitivity. It showed a good to excellent inter-rater reliability score, indicating that a previous training increases substantially the agreement between raters. Both the criterion validity and sensitivity were also analyzed comparing the changes in the RVGA score with variations in TDP for multiple sclerosis patients subjected to two different physiotherapy interventions. The results indicated that RGVA presents a good correlation with walking time and a fair correlation with stride length, as well as it proved to be sensitive to the evolution of patients' condition, despite not detecting significant differences between the two adopted strategies (Lord et al., 1998a, 1998b).

3.1.5. Edinburgh Visual Gait Score (EVGS)

The Edinburgh Visual Gait Score is a visual scoring system developed in 2003 to assess children with CP. This scale involves 17 gait parameters throughout the foot, ankle, knee, pelvis, and trunk for the sagittal, coronal, and transverse planes. EVGS utilizes a three point ordinal scale (0-2 according to the deviation degree) defining scores between 0 and 34 as signs of normal, moderate, and marked deviation (Read et al., 2003). It was designed to correlate well with instrumented gait analysis and functional scales (e.g. GMFCS and FAQ) as it has been repeatedly validated for good intra-observer and inter-observer reliability, presenting particularly higher scores for foot and knee parameters, making it one of the most modern and valuable observational gait indices (Araújo et al., 2009; Harvey and Gorter, 2011; Kulkarni et al., 2020; Read et al., 2003; Robinson et al., 2017, 2015; Viehweger et al., 2010).

3.1.6. Observational Gait Analysis (OGA)

The Observational Gait Analysis Index was developed in 2005 by Kawamura et al. to assess patients older than 8 years of age with spastic diplegic CP. OGA evaluates ten specific events in the three anatomic planes throughout the gait cycle, focusing on ankle, knee, hip, and pelvis (Kawamura et al., 2007). This index was analyzed by the same authors for inter-observer agreement and validity compared to 3D kinematic assessment. While inter-observer agreement was shown to be high, only two of the 10 assessed items (knee flexion at initial contact and pelvic obliquity) were shown to have similar results to the 3D kinematic data. The same authors suggested that other strategies should be considered in order to achieve better scores for the other parameters (Kawamura et al., 2007).

3.1.7. Salford Gait Tool (SF-GT)

The Salford Gait Tool is an ordinal scale designed to assess children with CP that was developed in 2007 (Toro et al., 2007a). SF-GT assesses the hip, knee, and ankle joints throughout sagittal angles in six distinct gait events. A tabled five-point scale (-2 to 2) is used to quantify the deviation degree for each event, enabling this way to evaluate the function of each joint over a gait cycle. The protocol for this index was developed with reference to quantitative kinematic data and iterated until it could more consistently agree with more advanced computer analysis (Toro et al., 2007a). Further studies by the same authors established relatively good inter-observer and intra-observer repeatability (Toro et al., 2007b).

3.1.8. Gait Assessment and Intervention Tool (G.A.I.T.)

The Gait Assessment and Intervention Tool is an extensive ordinal scale, covering 31 items divided into three sections: four items for upper limbs and trunk during both stance and swing phase, 14 items for trunk and lower limbs kinematics in stance phase and 13 items for trunk and lower limbs during swing phase. G.A.I.T. was developed in 2009 by a group of neurorehabilitation specialists to assess the performance improvement as the result of gait training interventions in subjects recovering from stroke events (Daly et al., 2009). As such, the proposed items were chosen to reflect the expected deviations to normal gait patterns in the three anatomical planes (0-3 according to deviation degree). G.A.I.T. intra- and inter-rater analysis showed respectively excellent and good reliability scores, allowing to discriminate the effects of the training interventions (pre/post treatment and between treatment groups). Two items were compared with instrumented data, obtaining a moderate to good correlation (Daly et al., 2009). In a posterior study, Zimbelman et al. evaluated the sensitivity of G.A.I.T. and POMA in the assessment of the recovery of stroke patients subjected to gait rehabilitation programs. The authors showed that G.A.I.T. was more sensitive to identify performance changes, being able to detect improvements in 91% of the analyzed subjects, while POMA only detected improvements in 59% of the cases. G.A.I.T. was even able to detect alterations in the most advanced stages of the training program (Zimbelman et al., 2012). Gor-García-Fogeda et al. analyzed the performance of the G.A.I.T. index in the study of multiple sclerosis patients. The obtained results indicate a high validity for this condition, presenting also an excellent intra- and inter-reliability score and the ability of detecting small changes (Gor-García-Fogeda et al., 2020b). In a posterior study, it was also shown the existence of an excellent agreement with RVGA and a moderate correlation with other functional mobility tests, such as Tinetti Gait Scale (TGS), Functional Gait Assessment, Hauser Ambulatory Index, Multiple Sclerosis Walking Scale-12, among others. However, a poor correlation was found for the TUG test and Modified Ashworth Scale (Gor-García-Fogeda et al., 2020a).

3.1.9. Stroke Mobility Score (SMS)

Considering the reported limitation in the assessment of post-stroke patients, Raab et al. proposed in 2020 a novel observational index for evaluation of this population. Stroke Mobility Score is defined by six non-redundant items that cover the trunk posture, movements of the upper and lower limbs for the affected side and the speed, fluency and stability of the gait. A four-point ordinal scale (0-3) with well-defined findings was proposed, based on the expected variations in the post-stroke gait. SMS presented a good-to-excellent inter-rater agreement and a high consistency. A strong correlation was found with functional scales, namely 10-Meter-Walk-Test, gait speed and TUG (Raab et al., 2020). Despite its reliability and ease-to-use, SMS can be seen as a stroke-specific index restraining its use in other conditions.

3.1.10. Other observational gait indices

The abundance of observational gait indices currently in existence has resulted in several becoming outdated, or failing to meet revision standards that consequently declare them invalid or unreliable. In several cases, authors of functional indices are simply unaware of further studies on their index, despite revisions and modifications to increase usability being suggested (Rathinam et al., 2014). Several observational gait indices that have been deemed unreliable, invalid, or have not had appropriate modifications were excluded from the main section and are briefly listed below.

Physician's Rating Scale: Abbreviated, Extended, and/or Modified Versions: As previously mentioned, there are substantial abbreviated, extended, or modified versions of the original PRS scale. This number is considerable and may surpass over a dozen developed over the last 20 years. Some of these modified scales are associated with partially validated indices, known for producing poor results or for not being appropriately assessed for inter/intra-observer reliability (Dickens and Smith, 2006; Rathinam et al., 2014). Consequently, few PRS-associated scales with more recent validations and assessments were highlighted above, and the rest are briefly summarized below. Some examples of these include the Modified Physician's Rating Scale (MPRS) (Ubhi et al., 2000), Abbreviated Physician's Rating Scale (APRS) (Flett et al., 1999), and VGAS (Dickens and Smith, 2006).

Observational Gait Scale (OGS): Developed by Araujo et al. in 2009 for children with spastic CP, the Observational Gait Scale assesses 24 items in three planes throughout the foot, ankle, knee, hip, and pelvis that were selected based on representative kinematic parameters (Araújo et al., 2009). From the comparison of 21 items with the corresponding 3D kinematic data, only five presented a good or very good agreement. Regarding intra- and inter-rater reliability, the index achieved respectively very good and good agreement scores. The lower values were observed in the frontal plane items and in pelvis. Despite being of potential value in assessing deviation from the norm, recent literature has stated the OGS to be inappropriate for children with CP, due to high inter-rater disagreement with established scales, such as the EVGS and VGAS (Bella et al., 2012).

3.1.11. Comparison of observational gait analysis tools

Thirteen gait indices were identified as worthwhile, established observational gait indices despite low reliability and/or validity. These indices can be easily modified to increase reliability and validity, enabling them to be more suitable for correlation with instrumented gait analysis techniques.

The reference to the original PRS arises from its historical significance, as it was one of the first indices to be widely accepted and applied by the medical community. Nowadays, it is most used to perform indices comparisons than to quantify pathology in gait. Few items are considered in its definition and its use is limited to a reduced number of cases, resulting in questionable inter-observer reliability and validity (Wren et al., 2005).

On the other hand, EVGS has become widespread mostly due to the high intra- and inter-reliability scores, even when applied by inexperienced raters (Ong et al., 2008). It covers a large number of items, which evaluate lower limbs and trunk performance in the three anatomical planes over the gait cycle. As result, EVGS is currently being applied towards the study of other age groups and disorders than those addressed in the original paper (Cretual et al., 2010; del Pilar Duque Orozco et al., 2016; Gupta and Raja, 2012; Ong et al., 2008; van Schie et al., 2005). Moreover, it has been successfully used in the evaluation of the outcome of specific interventions, such as the use of different types of orthoses (MacFarlane et al., 2020) or surgical procedures (Oudenhoven et al., 2019). SF-GT and PRS-OGS were also found to be good analytical indices, though their uses were more limited. As such, modifications to these indices would be beneficial to increase its usability across different age groups and pathologies.

WGS, RVGA and G.A.I.T are also mentioned due to their large application in the assessment of gait deficits in physical therapy. Similarly to EVGS, these indices evaluate the impairment level recurring to a tabled ordinal scale, varying in the number and assessed items. All the three scales proved to be sensitive in the detection of performance evolution after physiotherapy interventions, presenting also a good to excellent intra and inter-rater reliability (Daly et al., 2009; Guzik et al., 2020; Lord et al., 1998a, 1998b; Wellmon et al., 2015; Yaliman et al., 2014). From this group, G.A.I.T stands out as it was designed taking into account the limitations reported in literature for those indices. When compared with TGS or WGS, it covers a larger number of items, allowing also to score coordinated movement components of gait. Contrarily to RGVA, G.A.I.T was developed using objective guidelines, resulting in high intra and inter-rater reliability scores (Daly et al., 2009). However, although G.A.I.T. proved to be sensitive in the detection of performance evolution in stroke (Daly et al., 2009; Zimbelman et al., 2012) and multiple sclerosis patients (Gor-García-Fogeda et al., 2020a) and in target interventions using a lower limb exoskeleton (Puyuelo-Quintana et al., 2020), it requires more studies validating its applicability in other neurological conditions in order to be accepted as a general measure of gait pathology.

As expected, none of the identified indices were able to reproduce the same level of consistency of instrumented gait analysis (Grunt et al., 2010). In general, observational indices present good or better reliability scores for foot and knee sagittal parameters. On the other hand, hip and pelvis items tend to present lower scores, particularly in frontal and transverse planes (Araújo et al., 2009; del Pilar Duque Orozco et al., 2016; Kephart, 2020). Araujo et al. indicate that these differences could arise from the fact that hip and pelvis movements are a resultant of the combined motion of these joints, which makes difficult the visual perception of the rotation axes for all the planes. At the same time, the limited range of motion (RoM) of the pelvis in gait can also mislead the observer, leading to lower scores (Araújo et al., 2009).

The choice of the proper scale should consider the sensitivity of the index for the population and condition in study, as well as the items and score used in its definition. For instance, although WGS proved its value in the study of hemiplegia condition (Turani et al., 2004) and stroke patients (Guzik et al., 2020), it is defined using a limited number of items, restraining its use in other neurologic conditions (Daly et al., 2009; Rodriquez et al., 1996). Initially designed to assess different neurologic conditions, the score of each item in RGVA is fairly subjective, as specific guidelines (e.g. range of values, observations, etc.), which would assist the observer in the rating of the deviation degree, are not described (Daly et al., 2009; Lord et al., 1998b). Another aspect that can influence both the reliability and sensitivity of the index is the size of the scale used to score each item. Despite increasing its reliability, items defined using a lower number of categories tend to decrease the sensitivity of the index. Lord et al. compared the validity of the RGVA scale considering a three and four-point ordinal scale. The results confirmed that the reduction in one category in each item resulted in an increase of the index reliability. However, it is also referred that this adjustment could influence the sensitivity of the index to gait changes, reducing its general validity and applicability (Lord et al., 1998a).

A common idea that arises from this review is the influence of the rater experience and analysis methodology in the index score. Rigorous protocols, based on frozen or slow motion videos recorded with video cameras or smartphones, should be adopted to increase the reliability of the analysis (Aroojis et al., 2021; Kephart, 2020; Kulkarni et al., 2020). The use of a motion analysis video software is also recommended. Borel et al. showed that the use of a specialized software resulted in an increase of the inter-rater agreement, particularly in the items related with joint angles and timing measurements (Borel et al., 2011).

It is the authors' belief that a concerted-action by the scientific community, which defines detailed guidelines for the scoring of each item, would be beneficial as it will allow for the standardization in the application of the indices among medical, rehabilitation and biomechanics community. Similar initiatives were followed by other groups/ societies, such as the International Society of Biomechanics (ISB) or SENIAM project (Hermens et al., 1999; Wu and Cavanagh, 1995). Perceiving a lack of standards in the definition and reporting of kinematic data, ISB published a series of works describing guidelines for the definition of the segments and joints that compose the biomechanical models (Wu et al., 2005, 2002; Wu and Cavanagh, 1995). Visual references for the scoring of each item (e.g., anatomical landmarks to consider in segment definition, use of assistive panels, etc.) or guidelines for the acquisition protocol (e.g., video cameras position, acquisition frequency, use of freeze frame images, analysis methodologies, etc.) are examples of possible recommendations, allowing for the decrease of the reported intra and inter-rater variability. This initiative would allow also for the standardization of the indices scores acquired among different research centers and clinics.

3.2. Kinematics-based indices

3.2.1. Gillette Gait Index (GGI) or Normalcy Index (NI)

The Gillette Gait Index, otherwise known as the Normalcy Index, developed in 2000, is an index based on 16 parameters that can be separated into two groups: three TDP and 13 kinematic parameters defined in specific events of the gait cycle in the three anatomical planes. PCA is used to derive independent variables and make effective comparisons (Schutte et al., 2000). GGI allows for the measurement and calculation of deviations in gait between normal and pathological gait patterns. Originally designed for use in children and adolescents with CP, GGI has since been shown to be also effective in adults (Cretual et al., 2010). It is useful for patients with central nervous system pathologies (Syczewska et al., 2010), Guillain-Barré syndrome (Syczewska et al., 2021), adults with lower limb amputations (Kark et al., 2012) and anterior cruciate ligament deficiency (Liu et al., 2020). However, it should be noted that this methodology has various limitations, in particular, it is less effective for evaluating targeted interventions, it potentially requires a minimal sample size, and it exhibits high variability results when data is compared between labs (Cimolin and Galli, 2014; Tulchin et al., 2009).

3.2.2. Tingley's Scale for Young Children (TSYC) and Tingley's Extended Scale for Young Children (TESYC)

Tingley's Scale for Young Children is a data reduction technique based on Fourier transform and PCA that was developed in 2002. TSYC focuses on use of sagittal plane joint angles in the ankle, knee, and hip to understand variations from the mean in the gait of children. Notably, TSYC produces a score considering multiple joint angle curves as well as their derivatives, examining interactions between the different parameters and their intrinsic characteristics (Tingley et al., 2002). The final gait classification using this index can label gait as normal, unusual, or abnormal. Eponymously, TSYC is limited in use as it was designed for young children and on children up to age 7 who were born prematurely (Tingley et al., 2002). A validation and extension of this scale, Tingley's Extended Scale for Young Children (TESYC), was posteriorly designed in collaboration with some of the original authors, featuring similar concepts but incorporating additional kinematic and kinetic parameters from other planes of motion and a larger age group (up to age 13). Like the TSYC index, TESYC provides an overall score that classifies the subject's gait as normal, unusual or abnormal. It is composed of seven sub-indices, namely TSYC, Trunk Index of Gait, Kinematic Extra Index of Gait and four different kinetic gait indices, which individually assess different gait features (Chester et al., 2007a, 2007b). As this extended scale was not cited extensively and the authors wanted to continue expanding upon their methodology and index, it has not been included in this paper.

3.2.3. Gait Deviation Index (GDI)

The Gait Deviation Index, developed in 2008, is meant to be a general measure of gait pathology. It focuses on use of 15 gait features from 3D joint angles (hip, pelvis, knee, and ankle) throughout a stride cycle. GDI is a direct analog of the eigenface methodology and utilizes PCA to eliminate the natural correlation that occurs between the different index items. For a better interpretation of the index value, GDI considers a logarithmic transformation and conversion into a z-score, such as 100 points represents the average value for the control population and every 10 points below this value express one standard deviation (STD) from normal gait patterns (Schwartz and Rozumalski, 2008). Although GDI is fairly correlated to the aforementioned GGI methodology (Schwartz and

Rozumalski, 2008; Tsitlakidis et al., 2020), it does not require the same large sample sizes that GGI does (Schwartz and Rozumalski, 2008). Statistically, GDI can be described by a normal curve, allowing the application of parametric models during data analysis (McMulkin and MacWilliams, 2015; Schwartz and Rozumalski, 2008). It correlates also with other functional scales, such as FAQ, GMFM-66, GMFCS and five-times-sit-to-stand-test (FTSST) (Ito et al., 2019; Massaad et al., 2014; Molloy et al., 2010; Schwartz and Rozumalski, 2008; Tsitlakidis et al., 2020). GDI, thus far, has established validity for spastic CP, rheumatoid arthritis, muscular dystrophy, idiopathic clubfoot, Batten disease, degenerative spinal pathologies, X-linked hypophosphatemia, cervical spondylotic myelopathy, Williams syndrome, knee and hip arthroplasty, knee osteoarthritis and post-stroke hemiparetic gait (Esbjörnsson et al., 2014; Galli et al., 2012a, 2012b; Guzik and Drużbicki, 2020; Haddas et al., 2021; Ito et al., 2020; Jensen et al., 2015; Lööf et al., 2019; Maanum et al., 2012; Mar et al., 2020; Mindler et al., 2020; Naili et al., 2019b, 2017b, 2017a; Ropars et al., 2016; Schwartz and Rozumalski, 2008; Sienko Thomas et al., 2010). The index was sensitive to detect significant differences in spastic hemiplegic children using an ankle-foot orthosis (AFO), suggesting its validity to evaluate specific intervention in CP patients (Joanna et al., 2020). GDI was also able to differentiate pre- post-operative interventions in high-grade spondylolisthesis (Trivedi et al., 2021). However, it has been tested with lower limb amputees, patients with Parkinson's disease and hemophilia but limitations were found in these conditions (Galli et al., 2012a; Kark et al., 2012; Putz et al., 2020). Unlike GGI, GDI was unable to detect functional limitations between the different sides of lower limb amputees (Kark et al., 2012). It was also insufficiently sensitive to detect treatment outcomes for Parkinson's disease patients (Galli et al., 2012a). Despite these limitations, GDI has been hailed as a useful technique for cluster analysis and subject matching (Baker et al., 2009), and a good general measure of gait pathology (Cimolin and Galli, 2014).

3.2.4. Gait Profile Score (GPS)

The Gait Profile Score, as well as its deconstruction (Movement Analysis Profile (MAP)), is an index firstly presented in 2008 that generates a score to evaluate the gait performance and a map profile to analyze individually the deviations of the main kinematic variables. GPS represents the overall index score and was designed as the Euclidean distance between all gait features of the subject or group in analysis and a control dataset. On its turn, the MAP represents the variation of nine kinematic variables, referred as Gait Variable Scores (GVS), selected for both legs. Analogously to the GPS index, the GVS are described as the root-mean-square deviation (RMSD) across time between the subject/group in analysis and the reference data for each variable (Baker et al., 2009).

A validation study by the original authors found GDI and GPS to be closely related, with GPS more suitable for new models lacking large reference datasets (Baker et al., 2009; McMulkin and MacWilliams, 2015).In fact, GPS can be seen as a reinterpretation of the GDI score without adopting the logarithmic transformation and z-score conversion. Moreover, the calculation methodology used in GPS can be applied to any set of gait features, not being restricted to the ones selected in GDI (Baker et al., 2009). GPS is also moderately correlated to GGI (McMulkin and MacWilliams, 2015; Tsitlakidis et al., 2020). More similarly to GGI and unlike GDI, GPS was able to detect significant differences in the functional and amputated side of lower limb amputees (Kark et al., 2012). GPS and GVS have since been clinically validated and been suggested for uses in both clinical education and practice (Beynon et al., 2010; Bigoni et al., 2021; Bonnefoy-Mazure et al., 2020; Cansel et al., 2021; Carse et al., 2020; Cimolin and Galli, 2014; Ferreira et al., 2014; Galli et al., 2016; Ito et al., 2020; Kark et al., 2012; Ropars et al., 2016; Schweizer et al., 2014; Souza et al., 2020; Tsitlakidis et al., 2020).

3.3. Time-distance parameter-based indices

3.3.1. Functional Ambulation Performance Score (FAPS)

The Functional Ambulation Performance Score is an older system which originated as a three-part written test based on identifiable and measurable features of walking ability (Nelson, 1974). In 1998, technological advances enabled the development of a modernized FAPS, based on quantifiable TDP found throughout the gait cycle (Gretz et al., 1998). Since then, FAPS has been utilized and validated alongside the GAITRite System (Nelson et al., 2002), being applied in the evaluation of patients of all ages (Gouelle et al., 2011), with disorders such as Down syndrome (Gretz et al., 1998), multiple sclerosis (Givon et al., 2009; Hochsprung et al., 2020), Parkinson's disease (Hui et al., 2020; Nelson et al., 2002), chronic stroke (Peurala et al., 2005), diabetic foot (Sinha et al., 2020), among others. It has also applied to assess the alignment of prosthetic feet (Rajula et al., 2021) and the performance of foot insoles (Sinha et al., 2020). FAPS presented a fair correlation with 6MWT and a fair to good with muscle fatty degeneration in myotonic dystrophy Type 1 (Kim et al., 2020). The main limitation of FAPS seems to be that it is unsuitable for children under 12, as the gait parameters established for the technique are for adolescents and adults (Gouelle et al., 2011). FAPS stands to be improved but its validity for adolescents and adults is not in question (Gouelle et al., 2011).

3.3.2. Gait Variability Index (GVI) and Enhanced GVI (EGVI)

The Gait Variability Index is an index developed in 2013 to quantify fluctuations in TDP throughout the gait cycle (Gouelle et al., 2013). GVI was originally designed for Friedreich's Ataxia patients and utilizes the previously established GAITRite system (Gouelle et al., 2013; Nelson et al., 2002). GVI considers the use of PCA in nine spatiotemporal parameters to score gait deviations. This index was shown to be valid for both older children (12-18 y/o) and young adults (19-25 y/o) with Friedreich's Ataxia, presenting a correlation with International Cooperative Ataxia Rating Scale (ICARS) (Gouelle et al., 2013). A fair correlation was also found between GVI and the previously mentioned FAPS index (Gouelle et al., 2013). Balasubramanian et al. assessed the sensitivity and validity of the GVI by applying it in the study of an adult and elderly population (18-90 y/o) with different mobility impairments. Besides presenting an high inter-session reliability score (Gouelle et al., 2013), GVI proved to be sensitive in the evaluation of the effect of age in gait, allowing also to discriminate the patients by their level of mobility. Moreover, the results presented in this work showed that this index is fairly correlated with walking speed and with the Berg Balance scale, indicated its validity as a methodology to quantify gait variability in adult population (Balasubramanian et al., 2015). Studying a population of adults recovering from a stroke, Guzik et al. showed that GVI was able to identify significant differences both for the affected and non-affected leg, presenting also a moderate to strong correlation with functional mobility scales, such as 10-meter walk test, 2-minute walk test and TUG (Guzik et al., 2019). GVI proved its value as methodology to evaluate specific therapeutic interventions in spastic hemiplegic children, being able to perceive differences as result of the use of an AFO (Joanna et al., 2020). It has also successfully applied in the study of different neuromuscular and musculoskeletal conditions, such as multiple sclerosis (Kalron et al., 2017) and orthostatic tremor in Parkinson's disease (Opri et al., 2020).

However, Rennie et al. did not find significant differences while studying a population of patients with mild to moderate Parkinson's disease. Poor correlations were also found between GVI and functional mobility and balance tests, as well as it was not able to differentiate different severity levels. Thus, the authors concluded that the validity of the GVI for this patient population could not be confirmed (Rennie et al., 2017). Considering these findings, some of the GVI original authors proposed in 2018 an improved version of the index referred as enhanced GVI (EGVI). The new version was designed considering the reported limitations regarding the index magnitude (no comparisons can be done for values higher than 100) and the incapacity to depict the subject variability in the overall score (groups characterized by a low or high variability can result in the same GVI score) (Gouelle et al., 2018). Hence, four redundant items were removed from the index, as well as an adjustment in the calculation method was proposed. The enhanced version was applied in the same populations of the previous studies (Friedreich's Ataxia, children, older adults and Parkinson's disease), showing a strong correlation with the original version. Moreover, moderate correlations were found between EGVI and clinical tests related with balance and mobility performance for the older adults' population. A weak correlation was also found between the enhanced version and falls history for this population. Despite the changes in the index calculation, limitations were still found while evaluating the population with Parkinson's disease (Gouelle et al., 2018). Since then, EGVI was applied to predict the fall frequency in individuals with Parkinson's disease. Schmitt et al. showed that the EGVI was a better predictor of falls than each TDP individually (Schmitt et al., 2020). Similar results were obtained by Jabbar et al. while studying the EGVI for an Asian population with Parkinson's disease. The authors also showed that the enhanced version of the GVI correlates moderately with common functional mobility and balance tests, such as the TUG and FTSTS (Jabbar et al., 2020). EVGI has also able to detect differences on the gait performance of patients with degenerative cervical myelopathy (Kalsi-Ryan et al., 2020) and autosomal dominant cerebellar ataxia (Duque et al., 2021). However, more studies need to be performed to extend its validity to a large number of conditions/pathologies.

3.3.3. Toddle Temporal-Spatial Deviation Index (TTDI)

The Toddle Temporal-Spatial Deviation Index is an index developed in 2016 for the analysis of toddlers (18 to 22 months old). TTDI is a PCA-based index, which considers the use of seven TDP selected using a Kaiser-Meyer-Olkin measurement of sampling adequacy (MSA) for the calculation of a single score. As GDI, TTDI considers also a conversion into a z-score (Cahill-Rowley and Rose, 2016). The index was sensitive to detect differences in the gait patterns of preterm toddlers. TTDI presented an association with the Bayley Scales of Infant Development - 3rd Edition (BSID-III), resulting in lower scores for children with lower development scores, as well as with the GMFCs (Cahill-Rowley et al., 2019; Cahill-Rowley and Rose, 2016). Due to the final purpose of the index, TTDI is only validated for toddlers between 18 and 22 months old. More studies need to be conducted to extend the index application for a larger toddler/children population.

3.3.4. Pediatric Temporal-Spatial Deviation Index (TDI)

The Pediatric Temporal-Spatial Deviation Index is a PCA-based index proposed in 2019 that considers as inputs temporal and spatial variables (Zhou et al., 2019). It follows the same methodology proposed for GDI and was developed based on the TTDI (Cahill-Rowley and Rose, 2016) to be a generic screening tool for the evaluation of gait deviations in a pediatric population. It was initially implemented in the analysis of children with CP, presenting a strong correlation with GDI. TDI considers nine items per leg, which were selected according to its clinical and statistical relevance in the authors' dataset using the MSA test (Zhou et al., 2019). The index was sensible to detect significant differences between the control and pathologic groups. However, and despite presenting a similar trend, no statistical differences were obtained when compared with the GMFCS (Zhou et al., 2019). More studies should be performed in order to validate its use to a broader set of pathological conditions.

3.4. Kinetics-based indices

3.4.1. GDI-Kinetic

GDI-Kinetic is a direct analog of the kinematic-based GDI index that uses only kinetic measurements. The methodology involved in GDI-Kinetic focuses on the identification of features of raw kinetic gait data with singular value decomposition, and uses this data to compare and contrast the similarities and differences between the subject of interest and the control group. The methodology results in any differences being scaled and transformed to provide simplistic, statistically well-behaved measurements (Rozumalski and Schwartz, 2011). Overall, the 20 gait features identified through this method allow for integration of kinetic data with the kinematic data obtained through the original GDI method. Similarly, to the original GDI, GDI-Kinetic was able to distinguish FAQ levels and types of paralysis in CP patients (e.g., diplegia, hemiplegia types I-IV, triplegia and quadriplegia). However, the two indices present a low correlation, indicating that differences in the kinetic data could translate in different variations in the kinematic patterns and vice-versa (Rozumalski and Schwartz, 2011). GDI-Kinetic was applied in the study of CP (Brady and Kiernan, 2019; Kiernan et al., 2014), rheumatoid arthritis (Broström et al., 2013; Naili et al., 2017a), idiopathic clubfoot (Lööf et al., 2019) and total knee and hip arthroplasty (Naili et al., 2019b, 2017b). It was also used to assess the influence of the experimental errors during the center-of-pressure (COP) acquisition using force plates in the inverse dynamic analysis of gait and running in children. The authors inferred that errors until 12 mm in this measurement are acceptable for fast walking and running. However, they also concluded that for slower cadences, one should have attention to errors higher than 9 mm (Brady and Kiernan, 2020). While studying a population with knee osteoarthritis, Naili et al. showed that GDI-Kinetic was significantly lower in these individuals, presenting also a moderate to strong correlation with functional tests, such as the TUG, FTSTS and single limb mini squat (Naili et al., 2017a). However, in a posterior study, Naili et al. indicated that both the GDI and GDI-Kinetic were not able to discriminate different degrees of severity in this condition (Naili et al., 2019a).

3.4.2. Gait Kinetic Index (GKI)

Detecting a need for a kinetic index that could also be deconstructed to evaluate the different parameters individually, Cimolin et al. presented the Gait Kinetic Index, which is based on the GPS methodology. GKI considers six kinetic items per leg, namely ankle, knee and hip moments and mechanical powers on the sagittal plane. As for the GPS and MAP deconstruction, the RMSD between the target population and control group is computed for each kinetic feature and the outputs are posteriorly normalized by the minimal detectable change (MDC). The index was initially applied in the study of a population of children with diplegic CP, allowing for the detection of significant differences (Cimolin et al., 2019). A comparison between GKI and GPS shows a linear relationship with a low score. These results are similar to the ones observed when GDI and GDI-Kinetic were compared, supporting the idea that a change in the kinematic patterns could result in different kinetic patterns (Cimolin et al., 2019; Rozumalski and Schwartz, 2011). Due to the novelty of the index, few works apply this index in their analyses. More studies addressing its applicability in different pathologies and age groups should be performed to validate it for a broader use.

3.5. Kinematics- and Kinetics-Based Indices

3.5.1. Hip Flexor Index (HFI)

The Hip Flexor Index is a score developed in 2000 by the same authors of the GDI to assess the hip function of patients with CP (Schwartz et al., 2000). HFI takes into account segment/joint angles, rotation moments and mechanical powers in the definition of the score, applying the PCA methodology to derive independent variables and make comparisons effective. HFI considers five discrete kinematic and kinetic measurements in sagittal plane, but only those that relate to the hip function. The result is a single score established as a value that can quantify clinical alterations in hip function (Schwartz et al., 2000). As its name suggests, HFI is only useful for evaluating hip and pelvic interventions (Choi et al., 2011; Novacheck et al., 2002), limiting its usefulness to these specific interventions (Cimolin and Galli, 2014). More so, a directed change in the direction of normalcy does not necessarily indicate overall gait improvement, thereby preventing correlations between HFI score and patient gait functionality from being made (Cimolin and Galli, 2014).

3.5.2. Movement Deviation Profile (MDP)

Movement Deviation Profile uses a self-organizing map (a type of artificial neural network (Kohonen, 1990)) with various input measurements (joint angles, moments and powers of the lower limbs and pelvis) to learn a representation of the normal gait (Barton et al., 2012). The methodology output is a curve representing the distance to normality throughout a gait cycle. Further analysis through MDP highlights specific causes of a reported gait deviation, such as anatomical location and the timing of wrong gait patterns (Barton et al., 2007), making this a more powerful approach than other statistical methods. When compared with GDI and FAQ, MDP presents a high correlation score (Barton et al., 2012). Further studies of the same authors indicates that MDP is robust enough to perceive asymmetric responses, which are not considered by GDI (Barton et al., 2015a). In the last years, MDP was being successfully applied in the study of different conditions, such as Alkaptonuria (Barton et al., 2015b), patellofemoral pain (Ferreira et al., 2019), among others.

Despite being proposed for the analysis of kinematic and dynamic patterns of human gait, MDP methodology could be applied to any data expressed as a curve. An example is the application of the MDP in the study of the EMG patterns of muscle shoulder in patients with rotator cuff tears. In this study, a comparison of the correlation between a set of function scales is made with MDP outputs. The results indicate only a fair correlation with the Upper Limb Functional Index. The authors state that this absence of correlation could be related with the adoption of compensatory mechanisms at muscle level not perceived by the applied scales (Barton et al., 2013).

3.6. Electromyography-Based Indices

3.6.1. Kerpape-Rennes EMG-based Gait Index (KeR-EGI)

KeR-EGI index, developed in 2013, is based on electromyographic data and was designed to complement kinematic indices (Bervet et al., 2013). This measure was built with and tested on 59 healthy and 31 pathological adults of around 30 years of age, representing a variety of central nervous system pathologies. Bervet et al. designed this index as a quantitative complement for gait pathology based entirely on EMG data. KeR-EGI uses the same methodology as GDI but uses EMG profiles of seven muscles instead of joint angles to generate the final score (Bervet et al., 2013). The authors commented that sensitivity of the index had not been adequately tested due to the sample size used for the study. However, preliminary studies showed that Ker-EGI presents a good correlation with GGI and EVGS and fair with GDI. The index presented a good repeatability, needing yet more studies to understand the set of muscles that should be chosen to improve its robustness (Bervet et al., 2013). No papers discussing the validity or reliability of this index could be found. However, it was successfully applied in the study of a population with Duchenne muscular dystrophy and was able to identify significant differences between the control and patients group. It showed also a moderate correlation with Vignos functional scale, GDI and GPS (Ropars et al., 2016).

3.7. IMUs-Based Indices

3.7.1. Multifeature Gait Score (MGS)

Multifeature Gait Score (MGS) is an index that aims the assessment of gait quality considering a single IMU located at L3-L4 inter-vertebral level. MGS evaluates the gait performance according to six features, namely regularity, symmetry, temporal, distribution, amplitude and complexity. The overall score is posteriorly computed as the mean value of the six partial scores. It is important to note that MGS does not consider in its definition the usual kinematic parameters, such as the joint angular displacements in the three anatomical planes. The partial scores are computed using different methods based on the IMU measurements (10 features). Hence, the MGS was not considered a kinematic index in the present review. PCA and z-score transformation were applied in the index definition to remove redundant items and define its scale (Mansour et al., 2017). The index repeatability presented an excellent ICC for the global and four partial scores. The remaining two scores (symmetry and regularity) had a fair to good agreement. The index was tested in the evaluation of the gait performance of three populations, namely healthy adults, sedentary old adults and active old adults. MGS was able to detect significant differences between groups, presenting a lower score for the sedentary population followed by the active elderly and healthy adults groups (Mansour et al., 2017).

3.7.2. IMU-based Gait Normalcy Index (INI)

IMU-based Gait Normalcy Index (INI) was proposed in 2020 and intends to be a general score for clinical gait evaluation (Wang et al., 2021, 2020). The index is composed of three TDP and six kinematic features estimated from two IMUs located in the left and right shank. As in other indices, PCA methodology is used to eliminate possible correlations between the index parameters. The Euclidean distances of the uncorrelated variables that express the difference between the target and control groups are posteriorly calculated to obtain the overall score. The index was originally applied in the study of the rehabilitation process of a group of individuals suffering from N-hexane neuropathy. INI was able to detect significant improvements along the different rehabilitation stages. The authors stated that the index has potential to evaluate other conditions also characterized by gait deviations, such as Parkinson’s disease and post-stroke patients. However, further studies should be performed to validate its use in these pathologies. The index authors also suggested an adjustment to the index items, if the objective of the study is to infer the existence of gait asymmetries along the gait cycle (Wang et al., 2021).

3.8. Hybrid observational and instrumented indices

3.8.1. Gait Analysis and Motion Score (GAMS)

Gait Analysis and Motion Score (GAMS) is a hybrid index proposed in 2020 for clinical evaluation of gait. It considers ten observational items for both legs and five instrumented parameters. Each item is evaluated using a two-point scale (0-1) according with defined guidelines. The instrumented items include spatio-temporal (e.g., velocity, step length and width) and foot pressure parameters (COP evolution and foot rotation) measured using a pressure plate or instrumented treadmill. On its turn, the observational items focus on specific events along the gait cycle (e.g., toe clearance, knee position in sagittal plane, among others) and their score can also be supported by the experimental systems (e.g., initial contact and heel lift of the foot in terminal stance phase) (Dürregger et al., 2020). GAMS was applied in the study of a heterogenous population of 10 individuals recovering from a lower limb or spinal surgical intervention. The analysis of the inter-rater reliability showed an excellent agreement, even when only the observation indices were considered. The authors indicated that this fact can be in part explained by the adoption of a dichotomous scale. The index was able to detect differences between the individuals according with their gait performance. Despite considering items that can be easily measured, GAMS still requires experimental equipment, which can restrain its use in clinics and rehabilitation centers. Hence, the authors indicated that besides validating the scale for other conditions, they intend to develop an adapted version of the GAMS that does not consider instrumented parameters (Dürregger et al., 2020).

4. Discussion

The above-mentioned indices are each valuable in their own right. However, these indices are not all suitable for clinical implementation due to the affordability of technology, manpower, and time-consuming protocols involved. From a research perspective, the technological advances in the acquisition and processing systems, as well as the applied methodologies may play a role in whether or not these indices are feasible to implement. One goal of this paper was to elucidate both the clinical and research community on the wide range of gait indices currently available. With increasing amounts of authors citing observational gait scales, predominantly used in clinical settings, as subjective and poor alternatives to instrumented gait analysis (Kawamura et al., 2007), this information has become particularly relevant. Direct comparisons between indices are not always suitable, as these were originally designed for different applications. Nevertheless, the use of gait indices has been generalized, resulting in several works exploring the existence of correlations between different indices and scales and in the analysis of their sensitivity/specificity in the detection of gait abnormalities or characterization of a given disorder.

4.1. Indices usable in clinical settings

Clinically useable gait indices should be easily applicable and minimally time consuming, and for this reason, observational gait indices have been the main index type used in physician offices and rehabilitation centers. However, purely observational gait indices tend to be subjective; presenting in general only a fair correlation with kinematic data, particularly for parameters in horizontal and frontal planes (Grunt et al., 2010). Alternative, research-oriented indices have been proposed by several authors in order to obtain more quantitative and reliable results (Toro et al., 2003). Notably, both research-oriented and clinically focused indices are geared towards multi-age use and focus usability in long-term patient analysis. The majority of scales commonly implemented clinically are well-established observational scales. PRS, PRS derivatives, and EVGS are examples of such scales that have been integrated into clinical use over the years. Particularly, PRS was used for an extensive period of time, even while being extended, modified, or abbreviated. Derivatives of the PRS that have been validated, such as the aforementioned PRS-OGS, are still being implemented in both clinical and research-oriented settings. Scales such as the PRS-OGS are useful for clinicians due to simplicity and because all children within a pediatrics department could be assessed as the scale has been validated for ages 6 to 21 (Mackey et al., 2003). Similarly, EVGS, which is already popular amongst clinicians, has been validated and used with younger children, adolescents, and adults (Cretual et al., 2010; del Pilar Duque Orozco et al., 2016; Gupta and Raja, 2012; MacFarlane et al., 2020; Ong et al., 2008; Oudenhoven et al., 2019; Uzun Akkaya and Elbasan, 2021; van Schie et al., 2005) making it of clinical relevance as it can be used to assess patients over the long-term. EVGS has shown good correlations with the kinematic- (GGI, GDI and GPS) (Cretual et al., 2010; Robinson et al., 2017, 2015; Sardogan et al., 2020) and electromyography-based (KeR-EGI) indices (Bervet et al., 2013), maintaining its relevance in research settings. The use of EVGS in tandem with kinematic and electromyographic based indices allows for the most comprehensive data of a patient's gait.

Mostly applied in physical therapy community, WGS and RGVA proved also to be valid scales in the characterization of gait in pathology. Presenting in general a good intra- and inter-rater reliability, these indices have been used to evaluate with success variations in gait performance of patients subjected to training/physiotherapy interventions (Guzik et al., 2020; Lord et al., 1998b, 1998a; Pizzi et al., 2007; Turani et al., 2004; Wellmon et al., 2015; Yaliman et al., 2014). In a recent study, Guzik et al. showed that WGS can be even used to predict the symmetry index in patients recovering from a stroke event. In particular, the authors presented a regression model that relates the WGS items with the symmetry index calculated from time-distance and kinematic parameters. The model outcomes showed a strong to very strong correlation for the kinematic and temporal parameters, namely the RoM of the knee and hip in the sagittal plane and the stance phase time and distribution. However, a poor correlation was found for the spatial parameters (Guzik et al., 2020).

Presented recently, G.A.I.T. stands out as a valid measure to quantify gait disorders in pathology. Developed taking into consideration the limitations pointed out to RVGA and WGS, G.A.I.T covers a large number of items, which allow it to be applied in the study of different pathological conditions. It presents good to excellent agreement rates, being sensitive to discriminate also training interventions (Daly et al., 2009; Gor-García-Fogeda et al., 2020a, 2020b; Puyuelo-Quintana et al., 2020; Zimbelman et al., 2012). Despite its potential, G.A.I.T. requires more studies validating it in order to be generally accepted by the medical, physical rehabilitation and biomechanics community.

In general, clinicians tend to support their conclusions by means of observational indices. However, instrumented scales could also play an important role in the decision making. FAPS, GVI, EGVI and TDI are good examples of indices, which have been used in the evaluation of patients of all ages and disorders, since they do not require expensive and time-consuming protocols. FAPS, GVI and EGVI are sensitive to perceive small variations in spatiotemporal parameters, being accepted as good indicators of gait variability (Balasubramanian et al., 2015; Duque et al., 2021; Givon et al., 2009; Gouelle et al., 2018, 2013, 2011; Gretz et al., 1998; Guzik et al., 2019; Hochsprung et al., 2020; Hui et al., 2020; Jabbar et al., 2020; Joanna et al., 2020; Kalsi-Ryan et al., 2020; Kim et al., 2020; Nelson, 1974; Nelson et al., 2002; Peurala et al., 2005; Schmitt et al., 2020; Sinha et al., 2020). Finally, TSYC and its extension (Chester et al., 2007a; Tingley et al., 2002) are optimal for clinical use as they are one of the few instrumented gait scales that focuses on use with very young children. Moreover, its extension gives it long-term value for both clinicians within pediatrics departments and researchers. Integration of scales such as these into clinical settings would set the foundation for an easier transition between qualitative and quantitative gait scales.

IMUs systems are becoming more popular in clinical and rehabilitation environments, as these systems tend to be less expensive and complex than the traditional MOCAPs based on infrared cameras (Caldas et al., 2017). Following this trend, quantitative indices based on the use of IMUs have been proposed in the last years (Mansour et al., 2017; Wang et al., 2021, 2017). Despite the good results and their quantitative aspect, further studies need to be conducted to validate the use of these type of indices in the assessment of gait deviations in different pathologies/conditions.

4.2. Indices usable for research purposes

Not all indices are suitable for clinical use. In particular, certain indices with substantial time-consuming or computational components may be unattractive to clinicians. Research-based gait indices tend to be time consuming and require fully functional gait laboratories that demand substantial investments and personnel (Dickens and Smith, 2006; Harvey and Gorter, 2011; Narayanan, 2007). These indices often focus on complex computational methodologies and frequently require extensive reliability, sensitivity, and validity testing.

Instrumented gait analysis has long been established as the gold standard within gait index development. The most popular, well-established, repeatedly validated index methodologies within the kinematic, kinetic, dynamic, and electromyography-oriented fields are GGI and GDI. As previously stated, GDI is based on the GGI, and both methods are fairly correlated (Schwartz and Rozumalski, 2008; Tsitlakidis et al., 2020). They are based on PCA and are useful for the assessment of patients with a wide range of pathologies (McMulkin and MacWilliams, 2015). GGI is the senior of these two gait indices and despite being used in the study of different neuromuscular and musculoskeletal conditions, their items are chosen taking into account the expected variations observed in CP patients (Schutte et al., 2000; Wren et al., 2007). Several works referred limitations regarding its sensitivity to reflect the expected variations in the gait score, particularly in the assessment of targeted interventions (Cimolin and Galli, 2014; Danino et al., 2016; McMulkin and MacWilliams, 2015). The variability of this index to the input data is also addressed. Besides requiring a large number of control samples, GGI is highly sensitive to its source (McMulkin and MacWilliams, 2015; Tulchin et al., 2009). Tulchin et al. showed evidences that the overall value of GGI is strongly affected by the size of the database used to set the normalcy value. These authors calculated the GGI score considering the 16 original parameters for two group of subjects (able-bodied subjects and CP patients), showing that a minimum of 40 controls is required to obtain an error inferior to 20%. To achieve an error lesser than 10%, the authors estimated that the size of the sample should be higher than 96 controls. Tulchin et al. also indicate that the number of controls could be reduced, if the number of principle components is reduced. However, the type and the number of items, which can be removed or replaced without comprising the validity and sensitivity of the index, is referred by these authors as a challenging problem (Tulchin et al., 2009). Analyzing a group of children with CP, McMulkin et al. studied the variance of the GGI score to different control data gathered from four gait laboratories. The results indicated a high variability in the overall score both for the normal population and pathological subjects. In face of these conclusions, the authors suggested that the computation of the score should only use data retrieved from the same source. In case of different sources, the results should be analyzed from a relative perspective, i.e. the scores should be read as relative variations to the normalcy value rather than using absolute values (McMulkin and MacWilliams, 2015). Comparatively to GGI, GDI presents several advantages. Instead of considering discrete parameters in specific events, GDI evaluates the different items throughout the entire gait cycle. As a result, the global score reflects the variability of each item along the time, extending its applicability to other pathologies (Schwartz and Rozumalski, 2008). In the definition of the normal score, GDI requires also smaller sample sizes, being less sensitive to the input data (Cimolin and Galli, 2014). Despite this limitation, both of these indices are thoroughly comprehensive within their fields to the point that other indices, such as the KeR-EGI and GDI-Kinetic, have been designed to extend them (Bervet et al., 2013; Rozumalski and Schwartz, 2011).

Another research index widely accepted in the community is the GPS. Developed by some of the authors of the GDI and GGI, GPS considers a new approach to score gait abnormality. Besides generating a single score that is highly correlated with GDI, GPS allows also for the evaluation of each item individually (GVS). This fact enables to score the performance in each joint and anatomical plane, providing additional information on the quantification of the gait disorder (Baker et al., 2009; Souza et al., 2020; Tsitlakidis et al., 2020). By studying two population of patients suffering from Duchenne muscular dystrophy with kinematic differences at hip and pelvis level, Souza et al. showed that, besides providing more information, the GVS decomposition can even identify differences that the GPS overall score and GDI cannot perceive (Souza et al., 2020). Similar results were found by Cansel et al. while studying a population of patients suffering from hallux rigidus. The authors found significant differences in specific GSV items that were not perceived when only the RoM for the same joint was analyzed (Cansel et al., 2021). Comparatively to GDI, GPS does not require such a large database, being easily adapted to new models and items. In contrast, GPS does not present a normal distribution, since it does not consider the logarithmic transformation and z-score conversion followed in the GDI index (Baker et al., 2009; McMulkin and MacWilliams, 2015). It was being successfully applied in the study of different neuromuscular, rheumatologic and musculoskeletal conditions (e.g. Cerebral Palsy (Barton et al., 2015a; Bonnefoy-Mazure et al., 2020; Cimolin et al., 2011; Ferreira et al., 2014; Tsitlakidis et al., 2020), Parkinson (Galli et al., 2016), Duchenne muscular dystrophy (Schmitt et al., 2020; Souza et al., 2020), multiple sclerosis (Pau et al., 2014), lower limb amputees (Carse et al., 2020; Kark et al., 2012), Hallux rigidus (Cansel et al., 2021), Ehlers–Danlos syndrome hypermobility type (Celletti et al., 2013), neurologic flaccid and spastic conditions (Schweizer et al., 2014), post-stroke and hemiparesis (Bigoni et al., 2021), Charcot-Marie-Tooth (Coghe et al., 2020), Williams syndrome (Ito et al., 2020), poliomyelitis (Supiot et al., 2020), late-onset Pompe disease (Starbuck et al., 2021), among others), presenting also a high correlation with clinician rating scores, GMFCS and the FAQ scale (Baker et al., 2012; Beynon et al., 2010; Bigoni et al., 2021; Robinson et al., 2017). GPS and its decomposition have also been used as inputs for ANNs models, enabling the automatic identification of gait deviations and classification of CP children (Choisne et al., 2020).

The sensitivity of the gait indices is still an open issue. Their efficiency reflecting differences in the outcomes varies according to the pathology and condition in study. McMulkin et al. analyzed the sensitivity of GGI, GDI, and GPS indices by applying them in the study of seven children's groups with different gait pathologies. The results indicated that both GDI and GPS were sensitive to perceive differences resulting from different interventions. The authors concluded that GDI was the most sensitive index of the three, providing a global score that reflects the overall gait performance. On the other hand, GPS provided more information as it allowed to analyze also the effect of the treatment in each kinematic parameter (GVS). Despite being generally accepted as a valid index, GGI proved to be the less sensitive. The authors stated that there are no clear advantage of using this score compared to the two aforementioned indices (McMulkin and MacWilliams, 2015). Studying a homogenous population of 53 children with diplegic CP, Danino et al. showed the existence of significant improvements on temporal and kinematic parameters when an AFO was used. However, when the gait indices were analyzed (GGI, GDI and GPS), no significant differences were observed between trials. Even considering a division of the initial population by the GMFCS or the type of orthosis (solid or hinged), the reported variations did not result in significant differences in the three indices. The authors suggest that the differences noted in some items of the indices can be masked by the absence of variations in the others parameters, questioning the specificity and sensitivity of these indices in the evaluation of some interventions (Danino et al., 2016). In contrast with the previous findings, Syczewska et al. showed that GGI was the better index from these three to describe differences in a population suffering from Guillain-Barré syndrome. The authors indicated that this behavior could be a consequence of the way GGI was designed. It considers 13 discrete kinematic items and three spatiotemporal parameters, which were selected according with the expected variations in CP patients. Since Guillain-Barré syndrome is also a neurologic pathology, a CP specific index could be a better predictor of the gait changes in this type of conditions, while indices that evaluate differences along the gait cycle (e.g. GDI and GPS) can be seen as better overall predictors of gait deviations (Syczewska et al., 2021). This uncertainty in describing the observed variations could arise some concerns in the application of these indices. More studies should be performed in order to understand their limitations in the evaluation of targeted interventions, as suggested by (Danino et al., 2016), and to evaluate the pool of conditions and pathologies in which their application is valid. In a recent work, Barton et al. stated that the hip rotation should be excluded from the original set of input measurements considered in MDP index, as it allow for a better discrimination of the gait deviations (Barton et al., 2019). Moreover, since this index presents a high correlation with GDI and GDI with GPS, the authors indicate that a similar behavior could occur in these indices. However, further analysis should be performed to support this statement (Barton et al., 2019).

In a novel work, Syczewska et al. presented a new methodology for selection of the proper GGI items that better describe gait deviations for a given pathology. The authors considered different analytical methods, namely Hellwig correlation based filter, random forest and correlation techniques, to select the best 16 items from an initial list of 23 gait parameters. The methodology was applied in the study of a heterogeneous population including patients with spastic CP, idiopathic scoliosis and stroke patients. The results showed that the final list included several items that are not considered in the original GGI. For instance, the pelvis RoM in transverse plane, normalized step length and single stance phase are examples of items that are proposed to be included in the modified version of GGI for the CP population. The authors stated that this procedure has the main advantage of allowing for the simultaneous inclusion, as well as selection of different type of parameters (e.g. TDP, kinematic, kinetic and EMG variables), enabling the definition of a condition specific gait index (Syczewska et al., 2020).

Even more effective methodologies involve artificial neural networks. These methodologies are a well-established system that can be trained to map variables with respect to both gait and balance control through the use of pattern recognition. They often have superior subject classification recognition rates, sometimes as high as 100% (Wafai et al., 2014; Wu and Su, 2000). Recent studies have even shown that artificial neural networks, such as the MDP, can detect altered gait even when changes are missed by the GDI (Barton et al., 2015a). Consequently, artificial neural networks have become the most popular non-traditional methodology used in gait index development and gait analysis throughout the last decades (Chau, 2001). This methodology is expected to become increasingly popular, despite requiring substantial computational and mathematical components and significant amounts of data in order to produce reliable results.

It is important to note that besides the quantitative character of the instrumented indices, the computed scores are influenced by the quality of the input data and its base methodology. Studying the repeatability of GGI in healthy subjects, Assi et al. reported variations of 2° to 14° on joint angles, resulting in an uncertainty of $\pm$ 12 on GGI score. Using Monte Carlo simulations to generate random noise in CP patients' data, these authors showed that the propagation of errors due to uncertainties in the calculation of the different items can result in variations as higher as 100 points on the overall score (Assi et al., 2009). The results also indicate that the value of these uncertainties is not uniformly distributed amongst different levels of impairment. The influence of these errors in the overall score will increase with the abnormality degree of the subject in study, i.e. higher GGI scores will be more susceptible to errors in the input data (Assi et al., 2009; Massaad et al., 2014). In a similar work, however studying GDI index, Massaad et al. obtained a difference of 10 points between sessions, indicating that variations smaller than this value can arise from errors in the protocol application and limitations of the acquisition systems. The analysis of the propagation of errors using Monte Carlo simulations resulted in a narrow range of uncertainty values (0.8 for quadriplegia group, 1.3 for able-bodied group and 1.5 for hemiplegia group), attesting its robustness to different noise sources (Massaad et al., 2014). Moreover and contrarily to the GGI, the uncertainty level is not related with the abnormality degree. These advantages are a direct consequence of the type of scale (limited scale ranging from 0 to 100) and the nature of the items (use of the entire gait cycle rather than discrete events) considered in its definition (Massaad et al., 2014). Rasmussen et al. analyzed the intra-rater reliability and agreement for the GDI, GPS and GVS indices, by studying a population of 18 children with spastic CP. Considering a test-retest trial and three teams composed of two subjects from a pool of three, these authors obtained an excellent reliability and acceptable agreement for the GDI and GPS indices. However, when the different items from the GPS (GVS) were compared, a higher variability was observed, presenting only a fair to good reliability score. The results obtained for GVS also validate the idea that kinematic parameters taken from the sagittal plane present higher reliability scores, while the items from the transverse plane tend to present only fair to good scores (Rasmussen et al., 2015). The MDC was also analyzed in this work. Rasmussen et al. achieved a MDC value of 14.6 (18.5%) for GDI and 0.33 (13.3%) for GPS. The MDC for the GVS varied according with parameter in analysis, however the higher values were attained for pelvis tilt (1.27 (80.5%)) and pelvis rotation (1.25 (60.7%)) (Rasmussen et al., 2015). Similar results were obtained by Correa et al., while evaluating the GDI MDC in a population recovering from a stroke event (9.4 (13.0%) and 7.5 (15.8%) respectively for the affected and non-affected leg). The authors indicated that variations larger than the MDC need to be achieved in order to detect significant differences, questioning the validity of the GDI to evaluate this population (Correa et al., 2017).

A great number of works that apply indices resort only on observational or kinematic-based indices. However, when kinetic indices are compared with the analogous kinematic index, the results show a low correlation between them. This fact arises the idea that changes in the kinematic patterns could translate in different variations in the kinetic patterns and vice-versa (Cimolin et al., 2019; Rozumalski and Schwartz, 2011). Hence, the use of other types of indices, namely kinetic and electromyographic, could be beneficial to complement the kinematic information, allowing for a better characterization of the gait deviations.

4.3. Furthering indices

As expected, many indices still require substantial reliability and sensitivity analysis in order to validate them. While well-established indices such as EVGS, GGI, GDI and GPS had substantial validity testing, scales such as the G.A.I.T, HFI or the EGVI have had inadequate testing performed for the variety of applicable pathologies that exist. Other scales, such as the PRS-OGS and TSYC should be re-validated in a wider variety of age populations. It has been established that adult-like values occur around 11 to 12 years old (Gouelle et al., 2013), meaning that many indices may have unestablished, extended validity for older populations. Newer studies, such as the GDI-Kinetic, GKI and KeR-EGI, require generalized reliability, sensitivity, and validity testing that is not yet available. The vast majority of the aforementioned scales are unsuitable for definitive use until this testing has been completed. It would be particularly beneficial to see a review of PRS derived gait indices, as there are a variety of these listed under very similar names. Like the original PRS, the vast majority are now outdated, and modified versions should be established and validated. More so, a comparison of observational gait scales and their correlated kinematic, kinetic, or dynamic counterparts would be of benefit to the field of gait analysis. This would facilitate the process of moving from observational scale usage in the clinic to quantitative, instrumented analysis.

PCA and ANNs have proved their value as valid methodologies to compute a global score representative of a subject's gait. However, the use of other analytic methods could take the instrumented gait area one step further, as its use can provide new information that could be useful not only to quantify but also to characterize gait performance. Multiple correspondence analysis (Bonnefoy-Mazure et al., 2013) or spectral analysis (Gait Spectral Index (Héliot et al., 2010)) are examples of novel methodologies applied recently in the development of gait indices. It would be interesting to analyze their performance and their validity in face of the current indices to assess the advantages and limitations of these methodologies.

The methodology proposed by Syczewska et al. for the adaptation of the GGI index to different pathologies appears also promising, as it allows for the development of a condition-specific index (Syczewska et al., 2020). However, sensitivity studies should be performed to understand if the modified versions are able to reflect the expected deviations and to perceive the outcomes of the target interventions.

Other indices focused on the analysis of the variability of the kinematic patterns are also arising. Using the generalized principal motion analysis (GPMA) methodology (Iwasaki et al., 2019), an extension of the PCA for time-series data, Iwasaki et al. presented a novel approach for the evaluation of variability along gait cycle (Iwasaki et al., 2020a, 2020b). By analyzing the ellipsoids variability of the motion samples in the principal motion space, the authors can score the variability level of the trial and the way it changes independently of the walking speed. Nevertheless, despite its strong correlation with the mean standard deviation of the trials in analysis (Iwasaki et al., 2020b), further tests should be performed to allow for the validation of the methodology for different conditions and pathologies.

Lastly, as suggested in section 3.1.11, a concerted-action by the scientific community that properly defines general recommendations for the scoring of the different items would be relevant as it could standardize use of various indices, decreasing the reported inter- and intra-rater variability.

Despite the clear definition of the acceptance/exclusion criteria, the present study follows a narrative review approach aiming to identify and explore the different types of gait indices published over the last three decades. Hence, no meta-analysis was performed to directly compare the indices performance. Regarding this topic, it is important to note that some of the presented indices are still recent and others were only applied to a narrow number of pathologies, limiting this type of analysis to a wide range of conditions, as initially intended. Moreover, due to the large number of publications found during the identification and screening stages, no paper count was performed during them, which can hinder the reproducibility of the obtained results. Nevertheless, and to our knowledge, the present study is one of the first reviews to compile modern observational and instrumented gait indices, discussing their applicability and validity in clinical and research environments. It is the authors belief that this analysis summarizes the main issues related with the application of gait indices defined using different methodologies and considering different base technologies, supporting the members from these communities in the selection of the proper index for the population in analysis.

5. Conclusions

The last decades have shown a strong interest in moving past observational gait indices to usage of more complex instrumented gait analysis. Nevertheless, observational indices are still a common tool in clinical environments as they do not require complex, time-consuming and expensive protocols. EVGS stands out in this group, as it covers a large number of parameters, presenting also a good correlation with other kinematic indices. Moreover, its use was also validated for different age groups, enabling long-term assessments. Introduced recently, G.A.I.T. presents also a set of characteristics that can turn it in a reference in observational area, as it was designed to overcome the limitations of the current observational indices. Instrumented analysis is today the standard procedure in the analysis of movement. Supported by proper statistical methodologies, instrumented indices are useful not only to characterize gait but also to evaluate deviations to its normality. PCA-based indices, namely GGI, GDI and GVI, have been frequently applied, since this methodology allows for the computation of a score considering the possible correlations between the different items. Within this group, the GPS should also be highlighted. Besides providing an overall score representative of the gait performance, this index evaluates also each item individually, enabling a better characterization of the abnormality degree. In recent years, a new set of instrumented indices based on ANNs has been presented, showing promising results as these allow for detailed analysis over the entire gait cycle. Moreover, such indices can be trained using multiple inputs from different gait areas, presenting high recognition rates and making them very attractive in the classification and quantification of gait disorders.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix A. Supplementary data

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